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A Technological Learning Model in Joint R&D Projects in Petroleum Industries

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Highlights

- Effective factors and learning mechanisms of explorative and exploitative technological learning were identified during the joint R&D life cycle;
- A technological learning model in joint R&D projects in petroleum industries was presented;
- A mixed-method strategy using theme analysis and GRAY–DEMATEL–ANP was used.

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Abstract

Technological learning and the drive to self-sufficiency in different industries emphasize the role of companies in knowledge acquisition from external sources. Iran's petroleum industry is also a suitable case to study in this area, given the large firms on the one hand and the long-term historical partnerships with foreign companies on the other. Some of the industry's achievements, such as sustainability under sanctions, the country's largest source of export, and some recent breakthroughs, particularly in registering international patents and localization of various technologies, show the success of learning efforts. This study, which examines the learning processes for joint R&D (JRD) projects in the petroleum industry, analyzes the path of technological learning using a mixed-method approach and multi-case study method. For this purpose, 4 successful JRD projects in technological learning upstream and downstream are selected, and 16 interviews are conducted with project managers and experts of selected projects using the JRD life cycle to present a technological learning model in JRDs. The results of the theme analysis of interviews show that the most important and influential component of the model is "effective factors". The most affected component is "types of learning". Furthermore, the most influential factors and the most effective learning mechanism are "absorption capability", "cultural homogeneity", and "learning by interacting" respectively.

Keywords: Explorative Learning, Exploitative Learning, Learning Mechanism, JRDs Life Cycle

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1. Introduction

In recent decades, joint R&D (JRD) projects have been recognized as improving business competitiveness, reducing technology gaps, and strengthening the scientific foundations of firms and countries (Arranz and Fdez De Arroyabe, 2005). JRD is an agreement whereby parties organize R&D to offer new technologies and products to the market (Hagedoorn, 1993).

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JRD projects are essential for developing new products and services in uncertain, complex, and competitive environments (Faccin et al., 2016; Saenz and Pérez-Bouvier, 2014). Spanos et al. (2015) considered these collaborations an essential complementary tool for creating and utilizing the latest scientific developments.

Nowadays, the efficacy of technology transfer projects depends on the ability to accept and absorb the technology without outside help (Pandey et al., 2022). Without a learning strategy, achieving this objective is almost impossible (Liu et al., 2021). Technological learning in developing countries should be considered a fundamental concept influencing all technology transfer stages. The petroleum industry is technical, knowledge-based, expensive, profitable, and pivotal to managing consumption and achieving a knowledge-based economy.

Therefore, this study will explain the technological learning model in JRD projects in the petroleum industry. Hence, the researcher considered the share of explorative and exploitative learning in lifecycle stages, identified the factors and mechanisms affecting learning, and determined the interactions between the model's components.

2. Literature review

Nowadays, national development depends on industrial development, which relies on technology. Technological development requires a series of measures and abilities known as technological capabilities (Tahmasebi et al., 2017). Numerous studies have shown that technological learning is necessary for gaining these capabilities (Figueiredo, 2011; Peng et al., 2022).

Ghazinoory and Mohajery (2019) defined technological learning as an endogenous technological development approach that represents the organization's ability to respond to environmental changes by effectively absorbing foreign technologies and developing new technologies over time.

According to March (1991), collaborative learning covers explorative and exploitative learning:

- Explorative learning empowers companies to identify and interpret research information;
- Exploitative learning is to improve the ability to utilize knowledge during operations.

While exploitation-oriented companies aim for improved performance by focusing on production, exploration-oriented companies aim to create organizational flexibility through an open learning approach (Nielsen et al., 2018).

In recent decades, multiple empirical studies have attempted to identify the factors affecting learning, enabling companies in emerging economies to compete with companies in advanced and developed economies. According to the literature, various factors affect technological learning. Selnes and Sallis (2003) considered the level of trust between partners an essential factor in technological learning. In separate studies, Wagner and Hoegl (2006) and C. Lin et al. (2012) evaluated the absorption capacity of partners in technological learning. They concluded that absorption capacity significantly impacted technological learning and suggested improving absorption capacity before and during the collaboration. Numerous researchers have investigated the cultural and organizational homogeneity of partners in technological learning and considered it essential for facilitating technological learning in both parties (Johnson et al., 2004; Katila et al., 2008; Fang et al., 2011; Huikkola et al., 2013; Zadykowicz et al., 2020). Other factors discussed in the literature include a shared scientific basis (Huikkola et al., 2013) and market share between parties (Gaugler K and Siebert R, 2007). A similar organizational structure between partners is a positive factor in technological learning (Johnson et al., 2004; Huikkola et al., 2013; Reilly and Sharkey Scott, 2014; Bäck and Kohtamäki, 2016). Some researchers have acknowledged the negative effect of geographical distance on technological learning

(Weick et al., 2005; Fang et al., 2011; Zhang et al., 2018). The other factors whose effect on technological learning has been discussed in the literature include vertical and horizontal communication (Duso and Röller, 2010; B. Lin, 2014; Bäck and Kohtamäki, 2016) and diversity of communication channels (Corsaro et al., 2012; Reilly and Sharkey Scott, 2014; Kim et al., 2018; Arranz et al., 2019).

In addition to influential factors, the effect of learning mechanisms on the process is also essential. Table 1 summarizes the most crucial technological learning mechanisms and their characteristics.

Table 1

Technological learning mechanisms

Title	Example	Source
Learning by doing	• Tapping people's knowledge and experience in improving processes and products; • Identifying existing capabilities and formulating a suitable technology strategy;	(Von Hippel and Tyre, 1995; Saad, 2000; Bell, 2006; Tang, 2018)
Learning by using	• Applying the results of R&D to improve processes and products; • Reverse engineering; • Applying the innovations of other companies;	(Malerba, 1992; Kahouli-Brahmi, 2008; Lundvall, 2016)
Learning by searching	• Internal R&D; • An organizational R&D department; • R&D as a routine organizational activity;	(Saad, 2000; Bell, 2006; Tang, 2018)
Learning by interacting	• Innovation in collaboration with other companies and institutions; • JRD projects with other companies; • Licensed production, patent, and technical knowledge purchases;	(Saad, 2000; Lee, 2004; Figueiredo and Piana, 2018)
Science learning	• Using external information resources; • Attracting new developments in science and technology; • Learning from articles and patents;	(Tang, 2018)
Learning by direct instruction	• Holding employee training courses; • Holding training workshops; • Visiting top companies in the field;	(Ignatius et al., 2012; Jaoua and others, 2017)

As mentioned earlier, in this research, the factors and mechanisms affecting explorative and exploitative learning are identified in the lifecycle of JRD projects. JRD lifecycle means offering and exchanging complex services, including product design, feasibility studies, usability analysis, prototyping and testing, constructability analysis, and product customization (Huikkola, Ylimäki, and Kohtamäki, 2013). The JRD life cycle includes the following stages (Arranz et al., 2020; Arranz and Fdez De Arroyabe, 2005):

- Conceptualization, including determining needs and technological characteristics;
- Development, including technological development and prototyping;
- Operation, including technology commercialization, transfer, and diffusion;

The novelty of this study is the presentation of a suitable model for technological learning in JRD projects in the petroleum industries in developing countries, such as Iran. This is accomplished by recognizing existing scientific findings and the deepening technological learning in JRD projects while categorizing efforts by previous researchers. Due to budget constraints and the importance of improving industrial learning, analyzing collaboration learning (especially JRD projects) and presenting a model can be important for all stakeholders in technological R&D.

3. Methodology

This study's general approach is a mixed method. There are three stages in this study.

In stage one, by the literature review of technological learning in JRD projects, their lifecycle framework is considered for explaining technological learning in JRD projects in the petroleum industry.

Stage two used the multiple case study strategy and the semi-structured interview instrument to gain an in-depth understanding of technological learning in JRD projects in the petroleum industry. This study used the theme analysis method, which tries to analyze the content of interviews using the narrative process (Creswell and Clark, 2017). Hitchcock and Onwuegbuzie (2022) explicitly stated that a study of 4 to 10 cases is adequate. They warned that fewer cases would overlook the natural world's complexity, and more cases would increase the difficulty of the cognitive process. Therefore, the sample for the qualitative phase includes the following four projects in upstream and downstream JRD projects:

1. The 3-D petroleum system modeling in the Persian Gulf and Oman Sea (pearl program);
2. The quantitative and qualitative study of the Oman Sea gas hydrate sources (hydrate plan);
3. The demercaptanization of petroleum products by demercaptanization distillate (DMD-DMC);
4. The technology transfer, design, and construction of the natural gas odorant unit from gas condensates (odorant production process);

Semi-structured interviews with the project manager, vice-president, and two people spending the most time on each project and approved by the project manager were used for data collection. The interviews continued until the researcher achieved theoretical saturation. These interviews were analyzed by primary and secondary coding in Microsoft Excel. Over 403 codes were identified in the initial coding, which were later categorized into 17 secondary codes affecting the improvement of technological learning.

In stage three, the researcher-made questionnaire, Grey–DEMATEL[†] and the Grey–ANP[‡] method, will explain the causal relationships and the importance of the proposed technological learning model's components and subcomponents in JRD projects.

DEMATEL is a pairwise comparison decision-making technique first developed by Gabus and Fontela in late 1971, primarily to study complex global issues (Si et al., 2018). This model can reflect the interdependencies between variables and the properties and constraints in their relationships (Arce et al., 2015).

ANP is Thomas L. Saaty's mathematical theory to identify decision-making priorities among multiple variables without creating a unidirectional hierarchical relationship between decision levels (Mubarik et al., 2021).

Deng Ju-Long proposed the Grey system theory in 1982. As its basic premise, it was an uncertain system, and the related information is poor for system analysis or creating a description model (Li and Zhu, 2019).

[†] Decision-making trial and evaluation laboratory
[‡] Analytic network process

Finally, combining the Grey theory and DEMATEL–ANP is a suitable option for comprehensively evaluating the relationship between components and subcomponents.

Figure 1 presents a summary of the research process.

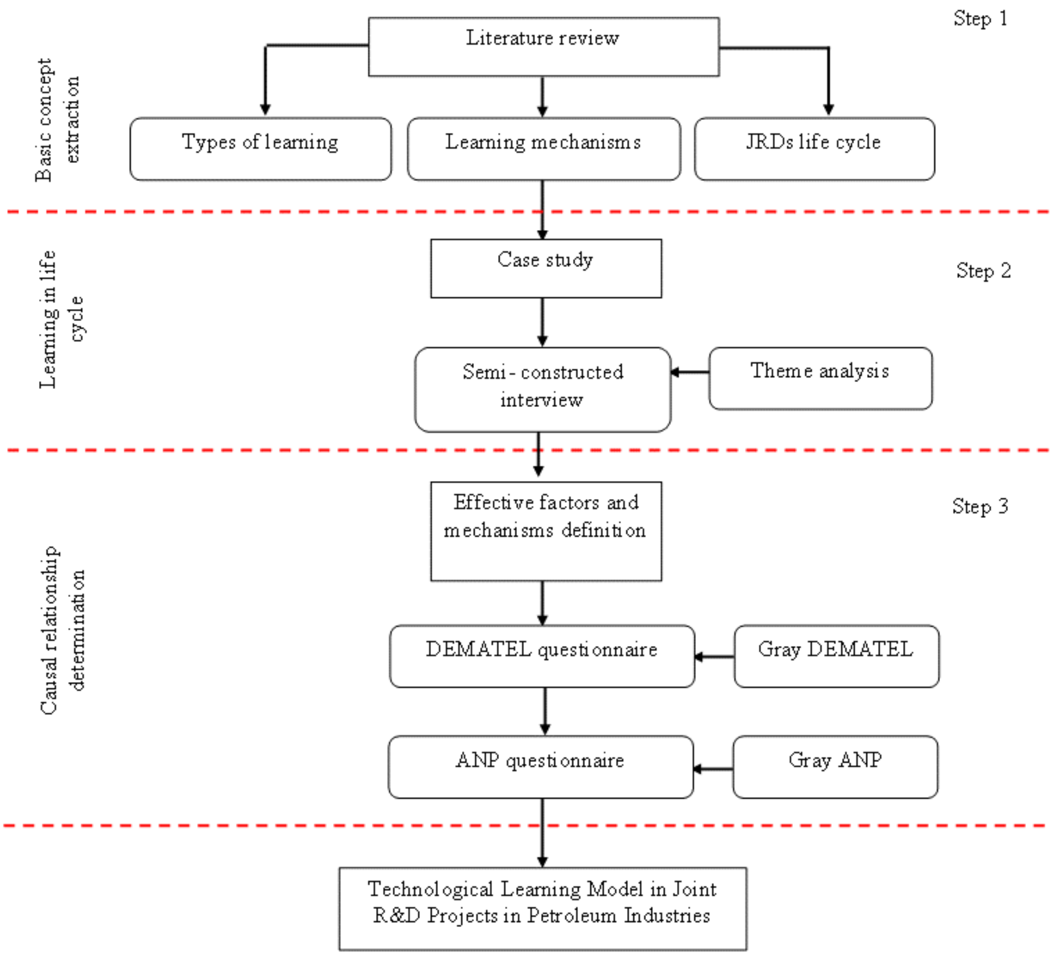

Figure 1

The research process

4. Results and discussion

This section reviews the research results for each project over its lifecycle stages.

1- The 3D petroleum system modeling in the Persian Gulf and Oman Sea (pearl program)

The Persian Gulf Pearl tries to generate and compose geological, geophysical, and petrophysical information and formulate a 3D model of hydrocarbon production, migration, and accumulation. This is accomplished using the world's most advanced software for identifying and discovering potential oil and gas reservoirs. Table 2 tabulates the results extracted from interviews for this project.

2- The quantitative and qualitative study of the Oman Sea gas hydrate sources (hydrate plan)

There are conventional and unconventional sources of gas. Due to the specific properties of the reservoir rock, unconventional sources are trapped and immobile, where oil and gas are produced. One such unconventional source is gas hydrates. Although it is easier and cheaper to extract oil and gas from conventional sources, the decrease in the world's conventional sources and the development of technologies for identifying and extracting unconventional resources have become more critical, and their utilization is growing worldwide. Therefore, the qualitative and quantitative project for analyzing the gas hydrate sources of the Oman Sea has been conducted as a JRD project between the Research Institute of Petroleum Industry (RIPI) and a Chinese company. Table 2 shows the various types of learning, the mechanisms affecting the cycle, and project influential factors extracted from interviews for this project.

3- The demercaptanization of crude using demercaptanization distillate (DMC-DMD)

Removing sulfur and mercaptan from mineral seal oil is essential in the petroleum industry. Removing environmental pollutants is crucial for implementing mercaptan removal processes in oil fields. About 15 years ago, RIPI partnered with a Russian company in the demercaptanization of mineral seal oil. In their memorandum of understanding, they jointly developed this technology. Thus, the DMD/DMC pilot with a daily capacity of 10 barrels was constructed in RIPI, and several research projects were executed. Table 2 lists the various types of learning, the mechanisms affecting the cycle, and project influential factors extracted from interviews for this project.

4- Odorant production based on the development of the demercaptanization process (odorant production process)

Natural gas is colorless and odorless, so an alarm substance is required to prevent leakage risks. As a result of their pungent smell, some sulfur compounds can be used as natural gas odorants. Due to their unpleasant odor and corrosion properties during storage and transfer, the light mercaptans in gas condensate create many problems and devalue this product. Therefore, RIPI and the same Russian company jointly started designing and constructing the natural gas odorant unit from gas condensates (odorant production process) in 2008. Table 2 tabulates the various types of learning, the mechanisms affecting the cycle, and project influential factors extracted from interviews for this project.

After studying the select projects and holding interviews, the main components of the proposed model were identified, as listed in Table 3.

Next, the relationship between the model's components and subcomponents was identified using a questionnaire. Cronbach's alpha was used to validate the data obtained from questionnaires, and its value of 0.91 for the model components suggested that the questionnaire should be valid.

Table 2

Summary of results from the Schlumberger projects

		External partner: French companies		Iranian partner: RIPI
			Learning type	**Learning mechanism**
Pearl program	Lifecycle Stages	Conceptualization	Explorative	Interacting–direct instruction
		Development	Explorative–exploitative	Interacting–doing
		Operation	Explorative–exploitative	Interacting–doing
	Effecting factors: absorption capacity, cultural homogenization, scientific basis, organizational structure, geographical distance, vertical/horizontal communication, communication channels, and collaboration goals			
Hydrate plan		**External partner: a Chinese company**		**Iranian partner: RIPI**
			Learning type	**Learning mechanism**
	Lifecycle Stages	Conceptualization	Explorative	Interacting–searching
		Development	Explorative–exploitative	Interacting–doing

		Operation	Explorative–exploitative	Direct instruction–doing
		Effecting factors: absorption capacity, cultural homogenization, scientific basis, organizational structure, geographical distance, vertical/horizontal communication, communication channels, and collaboration goals		
DMC-DMD		**External partner: a Russian company**		**Iranian partner: RIPI**
			Learning type	**Learning mechanism**
	Lifecycle Stages	Conceptualization	Explorative	Interacting
		Development	Exploitative	Doing
		Exploitation	Exploitative	Doing
		Effecting factors: absorption capacity, cultural homogenization, scientific basis, organizational structure, geographical distance, vertical/horizontal communication, communication channels, and collaboration goals		
Odorant production process		**External partner: a Russian company**		**Iranian partner: RIPI**
			Learning type	**Learning mechanism**
	Lifecycle Stages	Conceptualization	Explorative	Interacting
		Development	Exploitative	Doing
		Operation	Exploitative	Doing
		Effecting factors: absorption capacity, cultural homogenization, scientific basis, organizational structure, geographical distance, vertical/horizontal communication, communication channels, and collaboration goals		

Table 3

The main components and subcomponents of the technological learning model

Components	Subcomponents
Lifecycle of JRD projects	Conceptualization, development, and operation
Various types of learning	Explorative–exploitative
Learning mechanisms	Learning by interacting, learning by searching, learning by doing, learning by direct instruction
Effective factors	Absorption capacity, cultural homogenization, scientific basis, organizational structure, geographical distance, vertical/horizontal communication, communication channels, and collaboration goals

As mentioned earlier, the Grey DEMATEL method was used to determine the relationship between the model's components and subcomponents. Since DEMATEL uses the Grey logic, Table 4 presents the Grey numbers for calculation.

Table 4

The Grey values for calculating internal relations

Different values of linguistic words	Grey interval
Insignificant	[0–2]
Very low impact	[2–4]
Low impact	[4–6]
High impact	[6–8]
Very high impact	[8–10]

Table 5 and Figure 2 show that "lifecycle" and "effective factors" are definite causes in the proposed model, whereas "types of learning" and "learning mechanisms" are effects. The causes and lifecycle have the highest interaction with the other components.

The relationships between the subcomponents were also measured using the Grey DEMATEL method.

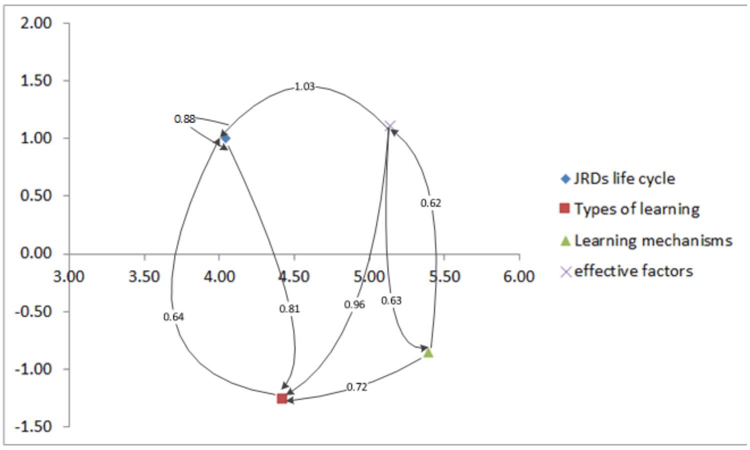

Figure 2

The causal network of the model's main components

Table 5

The (d + r) and (d – r) values of the dimensions of the technological learning model

	d	r	d + r	d – r	group
JRD project life cycle	2.52	1.52	4.04	1.01	cause
Types of learning	1.58	2.85	4.43	–1.27	effect
Learning mechanisms	2.27	3.12	5.39	–0.85	effect
Effective factors	3.12	2.01	5.13	1.11	cause

4.1. Lifecycle

The JRD life cycle has three main stages: conceptualization, development, and operation. The calculations indicate that the conceptualization and development stages are absolute causes that significantly impact learning in the other lifecycle stages. The operation stage is the effect of conceptualization and development. Table 6 and Figure 3 show the interactions.

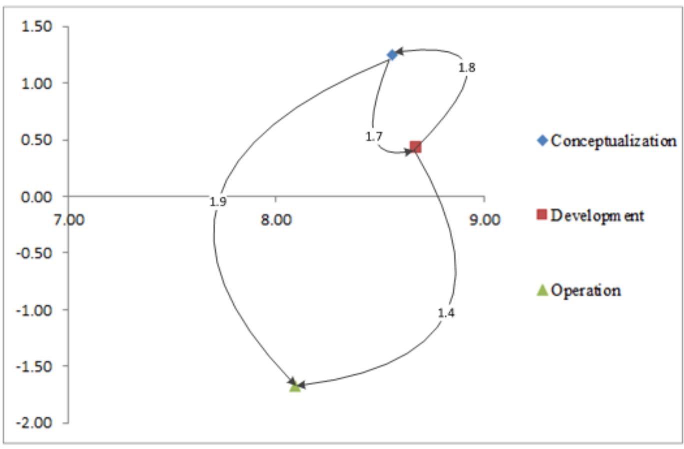

Figure 3

The causal network of JRD lifecycle stages

Table 6

The (d + r) and (d – r) values of the JRD lifecycle

	d	**r**	**d + r**	**d – r**	**group**
Conceptualization	4.91	3.65	8.56	1.25	cause
Development	4.55	4.13	8.67	0.42	cause
Operation	3.21	4.88	8.09	–1.67	effect

4.2. Types of learning

The calculations indicate that explorative learning is practical and exploitative learning is dependent. Therefore, explorative learning is the cause, and technological learning is the effect. Table 7 and Figure 4 show the interactions.

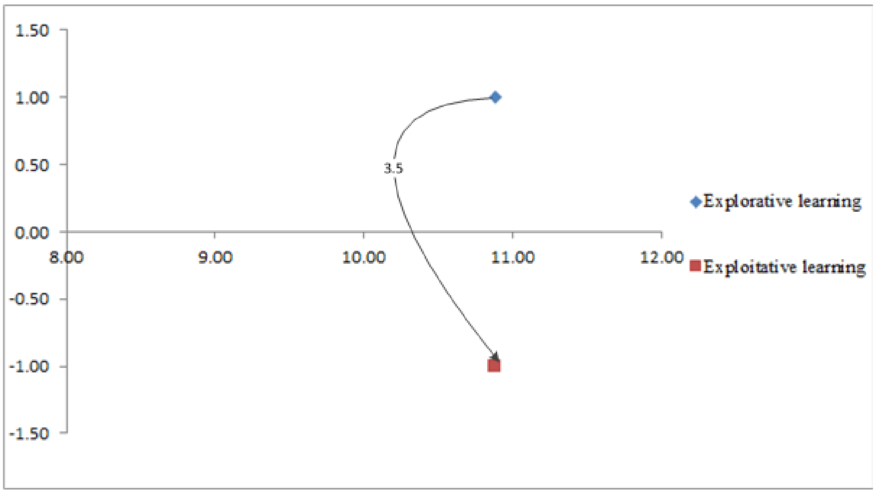

Figure 4

The causal network of types of technological learning in JRD projects

Table 7

The (d + r) and (d – r) values of types of technological learning in JRD projects

	d	**r**	**d + r**	**d – r**	**group**
Explorative learning	5.94	4.94	10.88	1	cause
Exploitative learning	4.94	5.94	10.88	–1	effect

4.3. Learning mechanisms

Four learning mechanisms were obtained in JRD projects in the petroleum industry via the theme analysis of interviews. After the calculations, “learning by interacting” and “learning by searching” were identified as causes, and “learning by doing” and “learning by direct instruction” were the effects. Table 8 and Figure 5 show the interactions.

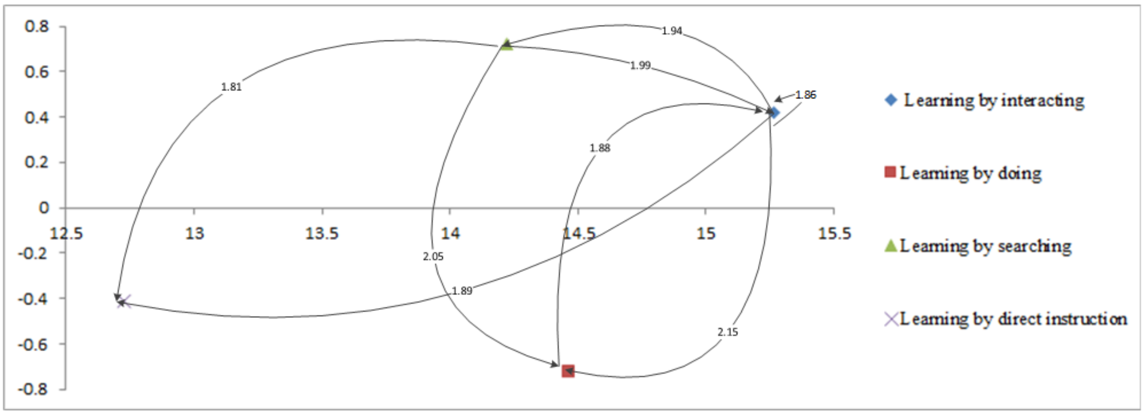

Figure 5

The causal network of technological learning mechanisms

Table 8

The (d + r) and (d – r) values of the technological learning mechanisms

	d	r	d + r	d – r	group
Learning by interacting	7.84	7.42	15.27	0.42	cause
Learning by doing	6.87	7.60	14.47	–0.73	effect
Learning by searching	7.47	6.75	14.22	0.72	cause
Learning by direct instruction	6.16	6.57	12.73	–0.41	effect

4.4. Effective factors

The theme analysis of questionnaires identified eight factors affecting technological learning in JRD projects in the petroleum industry. After the calculations, “absorption capacity”, “cultural homogeneity”, “geographical distance”, and “vertical/horizontal communication” were identified as causes; “scientific basis”, “communication channels”, “collaboration goals”, and “organizational structure” were identified as effects. Table 9 and Figure 6 show the interactions.

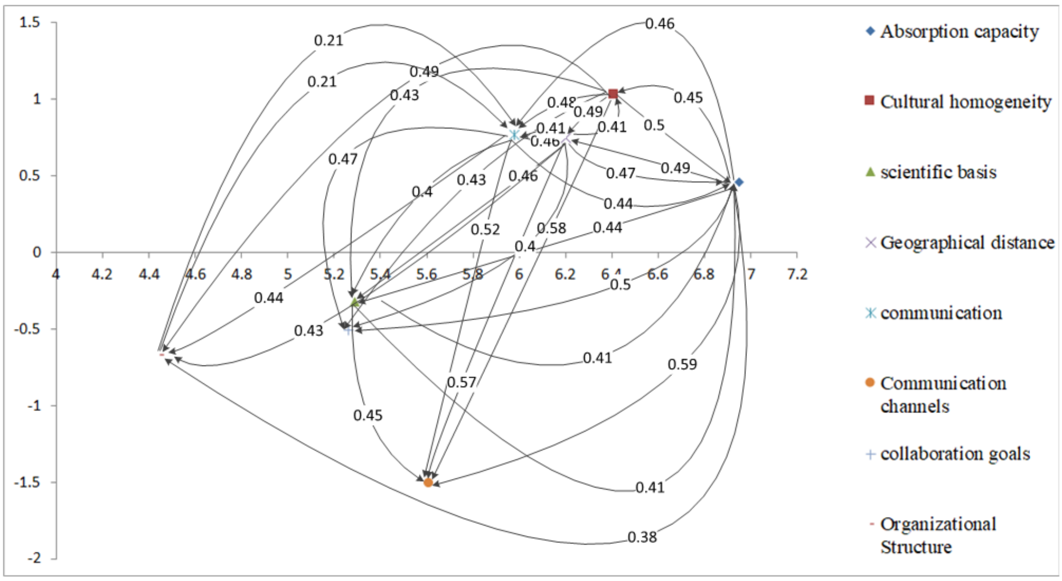

Figure 6

The causal network of factors affecting technological learning in JRD projects

Table 9

The (d + r) and (d – r) values of the technological learning mechanisms

	d	**r**	**d + r**	**d – r**	**group**
Absorption capacity	3.71	3.25	6.95	0.46	cause
Cultural homogeneity	3.72	2.69	6.41	1.03	cause
Scientific basis	2.48	2.80	5.29	–0.32	effect
Geographical distance	3.47	2.72	6.20	0.75	cause
Communication	3.37	2.60	5.98	0.77	cause
Communication channels	2.05	3.56	5.61	–1.51	effect
Collaboration goals	2.37	2.89	5.26	–0.51	effect
Organizational structure	1.89	2.56	4.45	–0.67	effect

As mentioned earlier, the ANP method was employed to determine the importance of components and subcomponents after determining the relationships between the model's components. At the same time, the Grey values were used for calculations to determine experts' opinions more accurately due to the uncertainty of the thesis.

Therefore, the importance questionnaire was filled out by experts. Since the cases of the study were projects, the questionnaires were completed by 16 interviewees.

Cronbach's alpha was used to validate the data obtained from questionnaires, and its value of 0.87 for the model components suggested that the questionnaire should be valid.

The unweighted supermatrix of the importance of the model's main components is shown in Table 10. The matrix shows that the "effective factors" are the most critical components of the model.

Table 10

The unweighted supermatrix of the main components

	JRD project life cycle	**Types of learning**	**Learning mechanisms**	**Effective factors**	**Eigenvector**
JRD project life cycle	1	0.16	0.46	0.94	0.29
Types of learning	0.83	1	0.02	0.01	0.07
Learning mechanisms	0.17	0.69	1	0.01	0.12
Effective factors	0.71	0.95	0.96	1	0.52

The unweighted supermatrix of the importance of lifecycle stages is presented in Table 11. It suggests that conceptualization should be the most critical lifecycle stage.

Table 11

The unweighted supermatrix of lifecycle stages

	Conceptualization	**Development**	**Exploitation**	**Eigenvector**
Conceptualization	1.00	0.95	0.95	0.51
Development	0.94	1.00	0.33	0.36
Operation	0.91	0.02	1.00	0.13

Table 12 indicates that both learning types are equally important.

Table 12

The unweighted supermatrix of the learning types

	Conceptualization	**Development**	**Eigenvector**
Explorative learning	1.00	0.80	0.51
Exploitative learning	0.76	1.00	0.49

Table 13 demonstrates that learning-by-doing and learning-by-interacting mechanisms are the most important.

Table 13

The unweighted supermatrix of the learning mechanisms

	Learning by interacting	**Learning by doing**	**Learning by searching**	**Learning by direct instruction**	**Eigenvector**
Learning by interacting	1.00	0.79	0.96	0.90	0.42
Learning by doing	0.87	1.00	0.94	0.96	0.44
Learning by searching	0.06	0.05	1.00	0.01	0.04
Learning by direct instruction	0.06	0.05	0.80	1.00	0.10

According to Table 14, "absorption capacity" and "cultural homogeneity" were the most important influential factors.

Table 14

The unweighted supermatrix of factors influencing learning

	Absorption capacity	**Cultural homogeneity**	**Scientific basis**	**Geographical distance**	**Communication**	**Communication channels**	**Collaboration goals**	**Organizational structure**	**Eigenvector**
Absorption capacity	1.00	0.92	0.86	0.74	0.91	0.62	0.62	0.89	0.16
Cultural homogeneity	0.59	1.00	0.85	0.88	0.67	0.83	0.89	0.82	0.16
Scientific basis	0.63	0.35	1.00	0.62	0.49	0.48	0.58	0.53	0.11
Geographical distance	0.93	0.64	0.89	1.00	0.89	0.60	0.56	0.57	0.14
Communication	0.58	0.48	0.71	0.64	1.00	0.79	0.56	0.51	0.12
Communication channels	0.65	0.50	0.75	0.93	0.29	1.00	0.47	0.43	0.11
Collaboration goals	0.45	0.59	0.87	0.44	0.43	0.83	1.00	0.70	0.12
Organizational structure	0.35	0.28	0.15	0.25	0.33	0.70	0.71	1.00	0.08

Figure 7 describes the proposed model using the study's qualitative and quantitative findings.

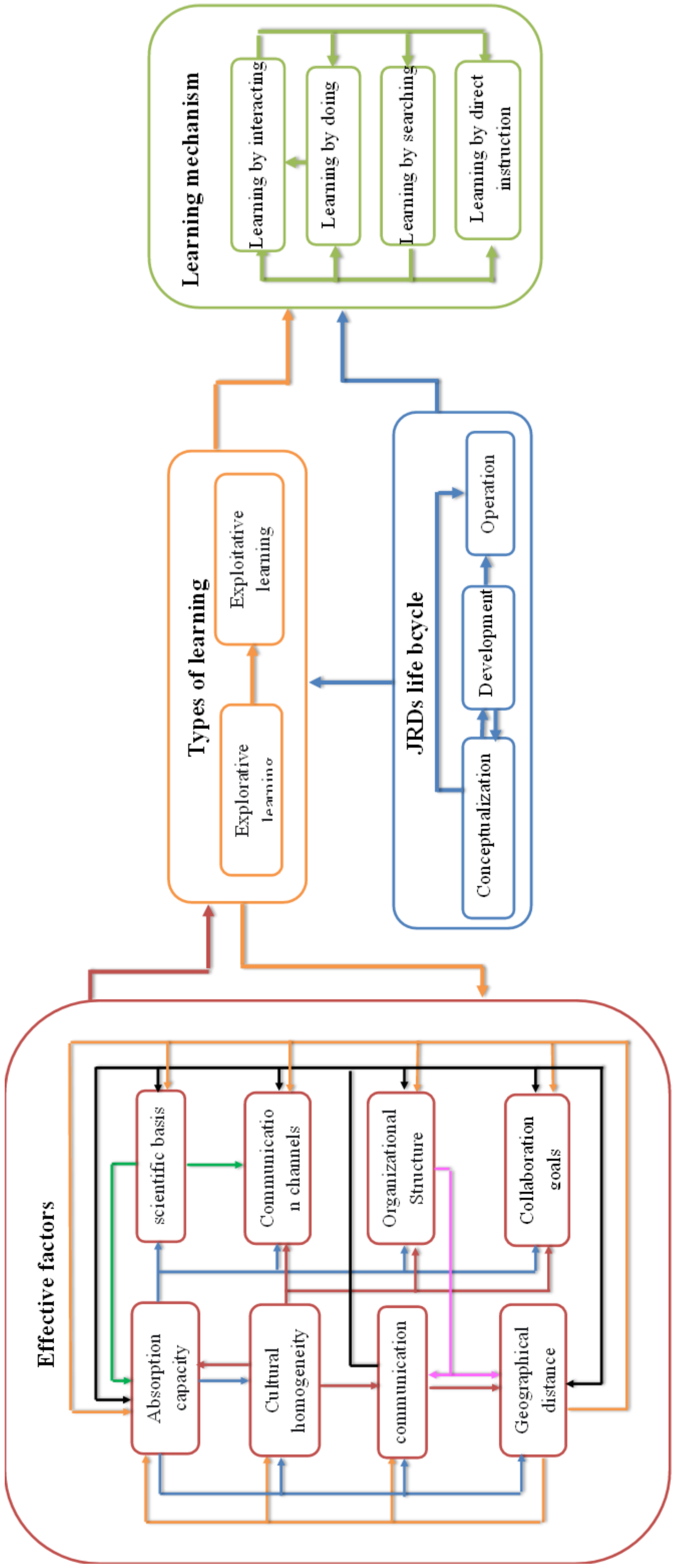

Figure 7

The technological learning model of JRD projects in the petroleum industry

5. Conclusions

In the qualitative section, the four selected JRD projects, namely two upstream projects and two downstream projects, were successful, and their team members were available for interview. The proposed research model's components expressed the researcher's observations with parts of interviews with managers and experts in direct and indirect narrations and quotations. Further, the qualitative section determined the hidden and visible mutual relationships between components and subcomponents. Discovering these relationships and understanding the main components allowed the researcher to present better and more accurate results. The first important point on technological learning in JRD projects was considering lifecycle stages. Although they were consecutive, the calculations indicated that the conceptualization stage affected the development and operation stages, and the development stage affected learning during the conceptualization and operation stages. Conceptualization was the most critical lifecycle stage, facilitating learning with more in-depth learning in other stages.

Evaluating explorative and exploitative learning in the four projects suggested that learning should be explorative in both upstream and downstream industries in the conceptualization stage. Since the novel topics under development were mostly JRD projects, assuming that the largest share of explorative learning belonged to the conceptualization stage was not unreasonable. In upstream and downstream industries, explorative and exploitative learning occurred in other lifecycle stages. Since the second and third lifecycle stages had a prominent operational dimension, this explained the occurrence of both learning types. Meanwhile, calculations indicated that explorative learning affected exploitative learning.

In addition to the life cycle and learning types, learning mechanisms were a significant issue in improving and facilitating learning. The interviews and calculations of learning mechanisms through learning by interacting and learning by doing were identified as necessary for technological learning in oil and gas JRD projects. They affected all lifecycle stages and explorative–exploitative learning and were strongly emphasized in downstream and upstream industries. Meanwhile, interviews also mentioned the learning mechanisms by searching and direct instruction. Although less critical in computations than the mechanisms described above, their role in learning could not be ignored.

In addition to the mechanisms mentioned above, influential factors were also identified during interviews, and the most crucial factor for interviewees was the organization's absorption capacity. The cultural homogeneity and geographical distance of partners followed them. The four selected projects implied that a greater absorption capacity led to more in-depth learning. The cultural homogeneity of the two collaborators also significantly affected learning. A shorter geographic distance indicated more accessible communication and more knowledge. The findings of the projects also suggested that a shared scientific basis between the collaborating teams, similar organizational structure, accessible communication without hierarchical bureaucracy, and the availability of different communication channels should also improve learning.

Therefore, any proposed learning improvement solution in JRD projects in the petroleum industry should consider their lifecycle and explorative–exploitative learning, select the suitable learning mechanisms, and feel the influential factors.

Nomenclature

ANP	Analytic network process
DEMATEL	Decision-making trial and evaluation laboratory

DMD	Demercaptanization distillate
JRD	Joint R&D
R&D	Research and development
RIPI	Research Institute of Petroleum Industry

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