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Mediation Model of Strategic Foresight Influencing Dynamic Capability

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Abstract: Strategic Foresight (SF) is required for an organisation in facing Volatility, Uncertainty, Complexity and Ambiguity (VUCA) environment to maintain relevant in future. There are many studies on application of SF by organisations in preparing for the unexpected. Especially, the relationship between SF and dynamic capabilities (DC) of an organisation. Thus, this study developed a mediation model which comprises of five exogenous constructs namely environmental scanning (ES); scenario planning (SP); knowledge creation (KC); culture (CU) and formal organization (FO), one endogenous construct of dynamic capabilities and one mediator construct of organisational learning capability (OLC). The data use to develop the model was derived from 209 respondents that participated in the questionnaire survey. The respondents were selected using a purposive random sampling technique amongst individuals who involved in decision-maker position of UAE organizations. The model was evaluated at measurement and structural components to achieve the fitness criteria values. It was found that the model has achieved GoF value of 0.8423 which indicates high overall validating power. This means that the model is rated as a high-quality model. After achieving these fitness criteria, hypothesis testing was conducted through bootstrapping function of the software. It was found that only two out of five of the direct effect relationships are significant, which are knowledge creation and formal organisation have significant relationships with the dynamic capabilities of the organisations. For mediation/indirect effect, it was found that organisational learning capacity as the mediator has significant effects toward three relationships which are scenario planning with dynamic capabilities; culture with dynamic capabilities and formal organisation with dynamic capabilities.

Keywords: mediation model, strategic foresight

1. Introduction

Inculcating dynamic capabilities of public organizations may become an important source of building institutional capacity to deal with future challenges (Chowdhury et al., 2019). The extant literature seems to reveal that, only a few empirical studies have been published on the relationship between strategic foresight (SF) and dynamic capabilities (DC) (Haarhaus and Liening, 2020). Although, there appears to be a plethora of studies on foresight and organizational capabilities, yet most of these studies are based on the case-study approach (Doz and Kosonen, 2008; Vecchiato, 2012, 2015; Rhisiart et al., 2015). Furthermore, the studies that do provide empirical evidence on relationship between foresight and capabilities (Ramirez et al., 2013; Paliokaite and Pecesa, 2015), seem to have considered foresight as a

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unidimensional construct. However, Haarhaus and Liening (2020), suggest that strategic foresight is a multi-dimensional construct, with five dimensions for example environmental scanning (SC), scenario planning (SP), knowledge creation (KC), culture (CU), and formal organization (FO). In this regard, there appears to be a dearth of studies on how the individual dimensions of strategic foresight influence dynamic capabilities of public organizations but not as a multidimensional construct.

A thorough and systematic review of the literature also reveals that the majority of the studies related to foresight of organizational capabilities have examined the association based on management and technological capabilities of organizations, using the resource-based view (RBV) (Murphy, 2021). However, the theory of dynamic capabilities was presented by Teece et al. (1997), where the authors addressed the limitation of RBV as an inflexible theoretical model. The authors argued that the dynamic capabilities view (DCV) moves the discussion forward, by suggesting that organizations will have dynamic capabilities if they can sense opportunities and challenges, and then seize upon them, and transform their organizational systems and structures in order to address these changes. So, far there seems to be insufficient empirical research on how the five dimensions of strategic foresight impact dynamic capabilities of organizations, based on DCV. Therefore, there appears to be a need to develop a nuanced understanding on the relationship between strategic foresight and dynamic capabilities, based on the theory of dynamic capabilities.

According to Semke and Tiberius (2020), there are many studies that have investigate SF and DC; however, the joint analysis of both concept in a single study is still under-explored. Generally, some studies have highlighted elements of these two concepts, such as Rhisiart et al. (2015) who showed that a firm’s engagement in scenario planning can support and strengthen elements of DCs. Also, Fergnani (2020) stated that SF can enhance the micro foundation of DC. Similarly, the study of Schwarz et al. (2020) showed that SF training is related to the micro foundation of the organization’s dynamic capabilities. Even though the study of Semke and Tiberius (2020) investigated the two concepts of SF and DCs in one study, this study was qualitative, and it did not provide any empirical findings. Therefore, the systematic investigation of the relationship between SF and DCs is scarce in past literature. This supports the direction and aim of the current study to bridge this gap by investigating the relationship between SF and DCs employing a quantitative design to test hypotheses in order to provide empirical findings and clear understanding of the relationship between these two concepts.

An important variable related to strategic foresight is organizational learning capability (OLC). In strategic foresight processes, a significant distinction has been made between individual and collective organizational learning. Bootz (2010) differentiates between foresight attitude, which relates to the cognitive aspects of anticipation and individual learning, and foresight behavior, which involves groups of individuals in more immersive learning within the organization. Concerning foresight attitude, it has been proposed that the cognitive skills of anticipation are centered on individuals, while collective learning is linked to organization policies and its direction to enhance learning across the whole organization (Rhisiart et al., 2015). This is also related to dynamic capabilities of the organization since gaining knowledge supports enhancing the human capital asset as an important resource of the organization’s dynamic capabilities (Rohrbeck and Schwarz, 2013). Despite the fact that authors refer to strategic foresight as a learning mechanism, little emphasis has been placed on the role of organizational learning in strategic foresight processes (Rhisiart et al., 2015). The gap which the current study aims to bridge is the use of organizational learning capability as a mediator between strategic foresight and dynamic capabilities. In other words, there is no clear evidence for any empirical study that has investigated organizational learning capability as a mediator between strategic foresight and dynamic capabilities of the organization.

2. Strategic foresight

Strategic foresight has emerged as a hot topic among management and futures researchers (Paliokaitė et al., 2014). The ambiguity, dynamism, and volatility of the evolving external market environment under which businesses work are caused by this (Vecchiato, 2015). Organizations are undergoing a number of political, economic, environmental, technological and social changes that affect customer preferences and require organizations to respond rapidly and sustainably (Chermack et al., 2001). Fast-paced product and business model developments, combined with market globalisation, are rising competition and pressure on productivity (Vecchiato, 2015). Changes and challenges are expected to increase as the world enters the information age. In order to thrive and potentially build and capture sustainable value, companies would need to develop their ability to creatively capture and synthesize relevant information into practical future-oriented knowledge (Paliokaitė et al., 2014).

As a result of this situation, foresight has turned into a significant logic for organisations operating in this fast-paced market setting (Paliokaitė et al., 2014), as well as an interesting research focus among scholars (Vecchiato, 2015). Although foresight research is relatively new and growing (Wilkinson, 2009; Amsteus, 2011), researchers have recognised the concept’s various and often contradictory conceptualisations (Sarpong et al., 2013; Paliokaitė et al., 2014). Prior studies have also shown that foresight activities and skills play a pivotal role in organisational success (Rohrbeck, 2012; Paliokaitė et al., 2014). Scholars, on the other hand, have lamented the lack of empirical studies on foresight and have called for an even more empirical and quantitative study of the term and its connection to firm results (Amsteus, 2008). In addition, Hideg et al. (2014) point out that the relationship between foresight practises and procedures is not empirically studied. However, few empirical studies have looked at the direct correlation between foresight and organization performance at the broadest level (Vecchiato, 2015), which is typically in large organisations with few exceptions (Jannek and Burmeister, 2007; Hideg et al., 2014). Nonetheless, we know little about the effect and importance of foresight activities, as well as the impact of environmental dynamism on firm results (Vecchiato, 2015).

Although the concept of strategic foresight has continued to gain popularity at the level of organisational research (Tsoukas et al., 2004; Sarpong et al., 2013), it has a certainly long presence in literature on management and futures markets. There is a controversial misunderstanding for this concept, however, since it is often referred to as a bundle of methodologies, often applied externally on an enterprise, in which companies can obtain a wider vision or test the future to assess possible competitive landscapes. An increasing number of organisations understand the importance of fostering strategic foresight and support and perform strategic foresight exercises on a regular basis, but they face challenges incorporating strategic foresight into their day-to-day operations (Rohrbeck, 2012; Nyuur et al., 2015). Simultaneously, strategic foresight is understood as embedded managerial competencies or skills manifest in the fabric of organisational life and upholstered in the ways of knowing and doing in an organisation, rather than as a collection of processes or resources.

2.1 Dimensions of strategic foresight

Strategic foresight enables the management of organizations to make informed decisions in the present with the short-term, medium-term, and long-term future in context (Murphy, 2021). Strategic foresight helps decision makers to make reasonable and relevant plans that will enable them to shape the future of the organization (Haarhaus and Liening, 2020). Such strategic capacity is knowledge-based and enables organizations to explore possibilities and the alternatives of the future that are likely to impact the mission and vision of the organization (Vecchiato, 2015). Treyer (2013) argues that foresight as a strategy is practice-oriented and is implemented for the collective effectiveness at organizational levels in order to make decisions on different aspects of their operations.

Vecchiato (2012) laments that foresight has been confused by many with the concept of forecast, which pertains to predicting the future based on past events or prior data. While foresight is about the ability of the management of an organization to strategically make decisions about the future, by trying to understand the changes in the horizon. Strategic foresight forwarded by Schwarz et al. (2020) refers to a set of organizational practices that are based on the five dimensions which are environmental scanning, scenario planning, knowledge creation, culture and formal organisation as elaborated below;

2.1.1 Environmental scanning

This factor refers to the existence of practices within the organization. Organizations with this aspect of foresight will have built in mechanisms whereby the organization is geared towards understanding and analysing the changes in the external environment (Haarhaas and Liening, 2020).

2.1.2 Scenario-planning

Scenario planning requires organizations to have planning systems in place that conduct various hypothetical scenario analyses. Such analysis may be done through mechanisms such as simulation, stress tests, etc. It enables the organization to develop different contingency measures against different possible outcomes (Schwarz et al., 2020).

2.1.3 Knowledge-creation

Knowledge creation requires that organizations have formal mechanisms to collect, analyse and synthesize data or information. The knowledge created by the organization enables it to visualize how the new knowledge will influence their future. Modern day tools such as big data analytics have mad exit much easier for organizations to create knowledge from data (Murphy, 2021).

2.1.4 Culture

This dimension of foresight refers to the existence of organizational culture that propels it to be future and forward thinking. Organizational culture is usually set, by the leaders of an organization. Such leaders ensure that their future-oriented thinking permeates downwards (Murphy, 2021). Culture has a profound effect on how the employees think and work, and thus it influences their response to change (Burt and Nair, 2020).

2.1.5 Formal organization

Formal organization refers to the existence of formal processes within the organization that propels the management to initiate future-oriented planning. The existence of such processes in the organization is essential for any realistic practice of strategic foresight (Schwarz et al., 2020). Therefore, this variable suggests the existence of formal procedures that are followed in the organization to analyse information about future, that are then converted to action plans (Burt and Nair, 2020).

2.2 Strategic foresight and dynamic capabilities

The perspective of dynamic capabilities explains why some businesses are able to predict and leverage possibilities through technological developments and rapid changes in their market space while others are struggling or going out of business (Teece et al., 1997). The ways in which businesses sense and capture possibilities lie at the heart of the theory of dynamic capabilities. Amit and Schoemaker (1993) concluded that superior market success stems from the combination that companies are able to create in their business environment between their internal strategic assets and the strategic factors of the industry.

Anticipatory activities in businesses, also known as Strategic foresight (SF), are supposed to lead to the willingness of a business to take new courses of action that are substantially different from the status quo and are theoretically capable of changing the game in entire industries (Gavetti and Menon, 2016; Rohrbeck and Kum, 2018). It has been shown that investment in such activities has a major positive impact on a company’s ability to see external trends earlier and respond on them faster (Schoemaker and Day, 2020). It has also been proposed that organisations with longer time horizons are better able to overcome managerial myopia and increase value (Flammer and Bansal, 2017). Innovative operations, as defined by Flammer and Bansal (2017), are a mechanism for long-term orientation, and strategic practices fall into the same vein as well.

Strategic foresight skills can be a wide variety of items, depending on the situation (Rohrbeck, 2010). Scenario planning has been recognised as a dynamic skill (Ramírez et al., 2013; Phadnis et al., 2015) for example, addressed scenario planning as distinct dynamic capabilities and early warning scanning work. On the other hand, Teece et al. (1997), in terms of sensing and shaping new opportunities, narrowly defined dynamic capabilities; related capabilities such as SF scanning, learning, and perception indicate that these activities can be interpreted as dynamic capabilities (Ramírez et al., 2013).

Since the late 1980s, the term foresight has been used to describe a normal human practice (Heiko et al., 2010). In organisations that advise and plan actions, the terms strategic, operational, and corporate foresight have been used somewhat synonymously and characterise anticipatory activities (Højland and Rohrbeck, 2018). Martin (2010) stressed that foresight is concerned with the long-term future; Vecchiato and Roveda (2010) coined the term strategic foresight to highlight the near connection between foresight and strategy (Coates et al., 2010).

The need to define a firm’s dynamic capabilities before analysing their potential effect complicates research on dynamic capabilities, which requires taking into consideration strategic foresight. The diverse capabilities approach, according to Teece et al. (1997), emphasises the development of management skills as well as difficult-to-imitate combinations of organisational, functional, and technical skills. Consequently, research in areas including research and development management, product and process development, technology transfer, intellectual property, manufacturing, human resources, and organisational learning is used in this field (Helfat et al., 2015). These areas show the importance of strategic foresight with dynamic capabilities in order to improve the performance of organizations.

The study of Kamal and Shawkat (2020) investigated the firm’s dynamic capabilities and how they affect knowledge management at diverse enterprises in Iraq's Kurdistan Region. It also aims to investigate the impact of employee experience on dynamic skills and knowledge management. Organizational dynamics was identified as one of the important markers of knowledge management based on the findings. Second, the data show that experience is a key moderator in the relationship between organizational dynamics and knowledge management.

In the context of the UAE, Pradeep et al. (2021) endorsed the development of a coaching method based on evidence-based decision making as a significant success element in establishing an innovation-oriented culture with agility at its centre in the UAE. This study shows that in the UAE, businesses are primarily motivated by streamlining operations or improving customer experiences; in either instance, businesses are effective in passing on the benefits to customers. The study’s overall findings show that businesses require a digital transformation framework and strategy to assess their current processes and strategies in order to smooth the success curve of their business using a need-based digital transformation that is appropriate for the time and environment, as well as an understanding of the economy’s macroeconomic dynamics, in which dynamic capabilities is a main factor in enhancing the organizational performance.

2.3 Organizational learning capability

Strategic foresight is the ability to accurately predict what will occur in the future and implement appropriate strategic plans based upon that knowledge for the purpose of improving organizational performance and serving the long-term goals. Strategic foresight is the application of strategic planning in the context and environment of an organisation. Scholars make a strong case that strategic foresight is not about predicting the future, but rather about preparing organizations for the future through a learning process (Bootz, 2010).

Strategic foresight and its strategies have been used to challenge mental structures and prevalent assumptions (Rohrbeck, 2012). Mental models enable organizations and individuals to manage and comprehend complex phenomena in ways that cannot be achieved without organizational learning. Mental models, on the other hand, must be challenged and renewed considering changing environmental conditions. Important signals can go undetected by the company's primary sensing activities, and companies have a propensity to view the environment through their own cognitive categories (Tsoukas and Shepherd, 2004). There has long been a fascination with how organizations consciously or unconsciously filter information, as well as how mental models react to weak signals of change (Kuosa, 2016). This can influence the organization's search direction and strategies in terms of what to look for and where to search for it, as well as managerial resistance to dissonant knowledge that does not fit with the dominant mental model (Boe-Lillegraven and Monterde, 2015). From the standpoint of organizational learning, the way organizations capture and use signals through a sensemaking framework is critical; however, opposite reasoning is thought to be critical in resolving cognitive biases in decision-making as well as improving better foresightful thinking, which necessitates organizational learning among staff (Rhisiart et al., 2015).

Strategic foresight allows decision makers to think strategically, immerse themselves in, and address the possible future problems by checking their existing future expectations in business strategy formulation (Sloan, 2019). Strategic foresight, according to Lusk and Birks (2014), assists decision-makers in understanding potential future complexity, building resilience, setting course, and then designing and implementing policies for the organization. During the strategy formulation process, foresight practises facilitate collective learning for improving the organization performance and for decision-makers as they adapt, execute, track, and review strategies with the aid of strategic foresight elements, which necessitates the participation of organizational learning.

Another aspect of the connection between Strategic Foresight and Organizational Learning Capability is that this complementary mechanism is typically guided by leadership (Bootz et al., 2019). To instil this competency as a mentality and a philosophy in the organization, leaders must practise it continuously before it becomes habitual. According to Schwarz et al. (2020), organizational learning capability necessitates routine scenario preparation, and similarly, organisational learning capability can promote strategic foresight by a greater understanding of expected strategies to support the organisation.

Building a learning community, personal mastery, and creating a shared vision are critical components for improving an organization's strategic foresight (Bootz, 2010). According to Burt and Nair (2020), organizational learning occurs solely by individuals, but the use of strategic foresight must promote learning as an organisational capability and as a part of its culture. The main point is that strategic foresight must be compatible with the multi-level learning states that are spread across the organization. When individuals, organizations, or the majority of workers in an organisation believe and practise strategic foresight, they can achieve this in the organization through fully follow the concepts of organisational learning. This demonstrates the importance of organisational learning in supporting strategic foresight and enhancing human capital as an important resource of the organization asset (Rohrbeck and Schwarz, 2013).

3. Conceptual Model

The model was based on three types of constructs namely exogenous/independent; endogenous/dependent and mediator as in figure 1. The endogenous consisted of five sub constructs of strategic foresight namely environmental scanning; scenario planning; knowledge creation; culture and formal organisation. While the endogenous construct is the dynamic capabilities of the organisation. Lastly, the mediator construct is the organisational learning capability.

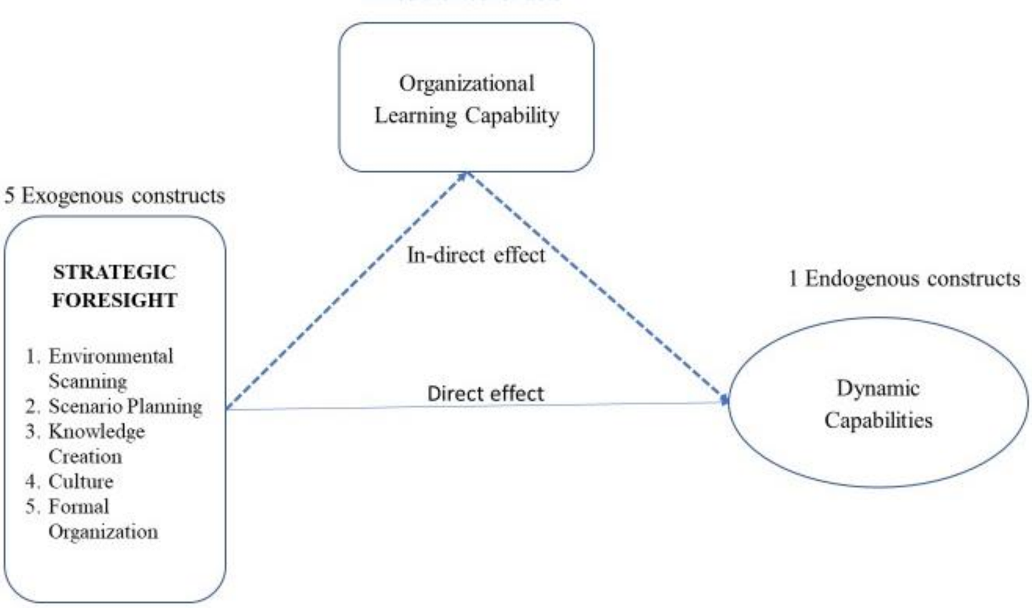

Fig. 1 - Relationship between the constructs

The model is intended to uncovered whether there is a direct relationship between strategic foresight with dynamic capabilities and also whether there is any indirect effect that cause by organisational learning capability toward the direct relationship. The constructs involved in the model are as in table 1.

Table 1 - Constructs of the model

Types of constructs	Name of constructs	Code and no. of factors
Exogenous	Environmental Scanning	ES-4
	Scenario Planning	SP-4
	Knowledge Creation	KC-4
	Culture	CU-3
	Formal Organization	FO-4
Mediator	Organizational Learning Capability	OCL-8
Endogenous	Dynamic Capabilities	Sen-5; Sez-4; Tran-5

4. Evaluation of measurement model (Outer model)

PLS-SEM demands that the measurement models meet specific quality requirements before evaluating the structural model. The first stage in evaluating the measurement models' reliability, convergent validity, and discriminant validity is to evaluate the measurement models' reliability, convergent validity, and discriminant validity. In the second step of the evaluation process, the measurement model's validity is determined. The two categories of validity that try to examine the research factors' outer model are convergent and discriminant validity (Hair et al., 2014). The Average Variance Extracted is used to determine convergent validity by looking at the factor loadings of indicators (AVE). The measures demonstrate that the indicators' variance measurement models are competent (Wong, 2016). The measuring models' discriminant validity is assessed using the Fornell and Larcker criteria, as well as the cross-loading of the outer models.

4.1 Convergent validity

Reliability refers to the degree to which a scale delivers consistent and stable measures across time, and it is related to reflective aspects in the measurement model (Hair et al., 2014). The measure of how free the scale is from random error is reliability, which is defined as the degree to which measurement scale answers are consistent across constructs (Pallant, 2011; Creswell, 2012). Although Cronbach's alpha is the most generally used measure of reliability (Awang, 2012), when working with PLS-SEM, composite reliability is favoured over Cronbach's alpha (Hair et al., 2011; Wong, 2016).

A measurement model must have a composite reliability of at least 0.7 to be considered reliable. (Wong, 2013). For newly constructed scales, however, a composite reliability of 0.6 is also regarded sufficient for establishing reliability (Chin, 1998, Hair et al., 2011, Bagozzi and Yi, 1988). Table 2 shows the methods for assessing model dependability.

Table 2 - Measurement models reliability

Items	OL	C. Alpha	C. R.	AVE
Environmental Scanning -ES	ES-1	0.781	0.567	0.836
	ES-2	0.838		
	ES-3	0.823		
	ES-4	0.530		
Scenario Planning- SP	SP-1	0.623	0.611	0.861
	SP-2	0.840		
	SP-3	0.861		
	SP-4	0.782		
Knowledge Creation- KC	KC-1	0.641	0.569	0.840
	KC-2	0.800		
	KC-3	0.800		
	KC-4	0.765		
Culture- CU	CU-1	0.969	0.683	0.854
	CU-2	0.965		
	CU-3	0.423		

Formal Organization- FO	FO-1	0.896	0.742	0.920
	FO-2	0.905		
	FO-3	0.846		
	FO-4	0.793		
Organizational Learning Capability- OLC	OLC-1	0.637	0.500	0.879
	OLC-2	0.747		
	OLC-3	0.786		
	OLC-4	0.679		
	OLC-5	0.586		
	OLC-6	0.524		
	OLC-7	0.800		
	OLC-8	0.727		
Dynamic Capabilities – DC	Sen-1	0.702	0.545	0.943
	Sen-2	0.749		
	Sen-3	0.770		
	Sen-4	0.701		
	Sen-5	0.653		
	Sez-1	0.817		
	Sez-2	0.738		
	Sez-3	0.793		
	Sez-4	0.825		
	Tran-1	0.843		
	Tran-2	0.800		
	Tran-3	0.798		
	Tran-4	0.632		
	Tran-5	0.398		

Table 2 shows the outcome of convergent validity. As can be seen, all of the goods have factor loadings more than 0.6, which is considered acceptable. All of the factors had AVE values greater than 0.5, which is the suggested value. Cronbach's Alpha and Composite Reliability scores are both higher than 0.7, which is the optimum value. As a result, all measurement models met the convergent validity requirements.

4.2 Discriminant validity

Discriminant validity assesses how different measurement models are from other research constructs. It evaluates how one measurement model compares to the structural model's other models (Memon and Rahman, 2013). Traditional discriminant validity evaluation methods include the Fornell and Larker criterion, as well as the Cross-loading criterion. According to Fornell and Larcker's (1981) criterion for proving discriminant validity, the square root of each measurement model's AVE must be greater than the model's correlation with any other model in the structural model. As a result, the square root of each outer model's AVE should be bigger than its correlation with any other construct (Hair et al., 2014), which is achieved in Fornell and Larker's test in the current investigation. Table 3 shows the results of Fornell and Larker's discriminant validity test.

Table 3 - Fornell-Laker's test

Constructs	Code	CU	DC	ES	FO	KC	OLC	SP
Culture	**CU**	**0.826**						
Dynamic Capabilities	**DC**	0.577	**0.838**					
Environmental Scanning	**ES**	0.481	0.530	**0.753**				
Formal Organization	**FO**	0.545	0.837	0.506	**0.861**			
Knowledge Creation	**KC**	0.475	0.781	0.504	0.726	**0.794**		
Organizational Learning Capability	**OLC**	0.666	0.741	0.524	0.663	0.584	**0.792**	
Scenario Planning	**SP**	0.513	0.594	0.452	0.473	0.491	0.716	**0.782**

The second test for discriminant validity is the cross-loading test. The cross-loading criterion was advocated by Chin (1998). According to the criterion, items must load greater on their underlying constructs than on other constructs (Hair et al., 2014; Wong, 2016). Table 4 shows that each factor in the current study had a higher cross loading on itself than the other factors, suggesting discriminant validity.

Table 4 - Cross-loading assessment

	Code of constructs						
Factors	**CU**	**ES**	**FO**	**KC**	**OLC**	**SP**	**DC**
CU-1	**0.969**	0.443	0.517	0.461	0.656	0.483	0.544
CU-2	**0.965**	0.453	0.533	0.443	0.647	0.511	0.568
CU-3	**0.723**	0.285	0.238	0.236	0.239	0.212	0.250
ES-1	0.261	**0.781**	0.362	0.322	0.348	0.339	0.350
ES-2	0.456	**0.838**	0.496	0.444	0.464	0.373	0.507
ES-3	0.364	**0.823**	0.344	0.403	0.423	0.399	0.396
ES-4	0.341	**0.730**	0.287	0.328	0.319	0.228	0.308
FO-1	0.473	0.427	**0.896**	0.647	0.630	0.457	0.768
FO-2	0.493	0.414	**0.905**	0.597	0.626	0.449	0.746
FO-3	0.397	0.448	**0.846**	0.591	0.515	0.326	0.650
FO-4	0.512	0.461	**0.793**	0.670	0.502	0.386	0.712
KC-1	0.352	0.342	0.480	**0.741**	0.453	0.544	0.522
KC-2	0.383	0.365	0.573	**0.800**	0.435	0.322	0.577
KC-3	0.391	0.439	0.549	**0.800**	0.464	0.323	0.610
KC-4	0.305	0.367	0.583	**0.765**	0.408	0.303	0.639
OLC1	0.423	0.295	0.450	0.421	**0.730**	0.414	0.479
OLC2	0.445	0.344	0.538	0.416	**0.744**	0.523	0.613
OLC3	0.564	0.448	0.581	0.497	**0.786**	0.537	0.616
OLC4	0.505	0.392	0.450	0.333	**0.792**	0.570	0.476
OLC5	0.356	0.346	0.237	0.245	**0.795**	0.479	0.354
OLC6	0.267	0.258	0.220	0.205	**0.744**	0.585	0.290
OLC7	0.562	0.425	0.575	0.530	**0.790**	0.509	0.644
OLC8	0.496	0.363	0.519	0.516	**0.713**	0.362	0.550
SP-1	0.236	0.202	0.363	0.486	0.461	**0.723**	0.517
SP-2	0.532	0.404	0.463	0.423	0.662	**0.840**	0.553
SP-3	0.443	0.428	0.348	0.349	0.588	**0.861**	0.427
SP-4	0.350	0.362	0.266	0.246	0.488	**0.782**	0.314
Sen1	0.374	0.421	0.694	0.670	0.504	0.446	**0.793**
Sen2	0.388	0.375	0.674	0.594	0.528	0.361	**0.880**
Sen3	0.431	0.381	0.701	0.610	0.518	0.358	**0.791**
Sen4	0.340	0.295	0.619	0.544	0.516	0.337	**0.780**
Sen5	0.370	0.447	0.512	0.570	0.551	0.504	**0.851**
Sez-1	0.400	0.403	0.621	0.654	0.556	0.516	**0.818**
Sez-2	0.395	0.348	0.533	0.517	0.500	0.449	**0.839**
Sez-3	0.412	0.424	0.655	0.641	0.569	0.428	**0.794**
Sez-4	0.477	0.419	0.702	0.619	0.558	0.378	**0.826**
Tra-1	0.509	0.430	0.695	0.659	0.564	0.446	**0.844**
Tra-2	0.468	0.392	0.645	0.613	0.579	0.426	**0.800**
Tra-3	0.441	0.367	0.647	0.568	0.569	0.448	**0.798**
Tra-4	0.595	0.463	0.561	0.434	0.693	0.595	**0.830**
Tra-5	0.373	0.309	0.234	0.229	0.506	0.578	**0.794**

As a result, as shown in tables 3 and 4 above, this study used the two previously established discriminant validity evaluation criteria to determine the uniqueness of each measurement model. The square root of each measurement model's AVE is greater than the correlation of the model with all other constructs in the structural model, according to Fornell and Larcker's test. In addition, Table 4 shows the results of discriminant analysis with the cross-loading criterion. The items' loadings on their structures are indicated by bold values. Higher-order structures are indicated by yellow highlighted values. All objects load more on their underlying constructions than their cross-loadings with other constructs, as shown by the result. The measurement models attain discriminant validity as a result of this criterion.

5. Evaluation of structural model

In the second stage of the PLS-SEM evaluation criteria, the structural (inner) model is assessed (Hair et al., 2014). The causal links between the measurement models are established in the structural model (Hair et al., 2014). The described interrelationships are intended to provide answers to research questions and to test research hypotheses. The fundamental purpose of structural model evaluation is to determine the model's quality and rate its capacity to predict endogenous constructs. The bootstrapping procedure is used to assess the path coefficients and their significance; the endogenous construct's coefficients of determination (R2); the exogenous measurement model's effect sizes using Cohen's f2; the model's predictive relevance using cross-validated redundancy (Q2); and the model's global goodness of fit (GoF) (Hair et al., 2011; Hair et al., 2014; Wong, 2016).

5.1 Path coefficients evaluation

The goal of PLS-SEM is to forecast the causal relationship between study exogenous constructs and endogenous constructs, which are generally expressed in hypotheses. The hypotheses are checked using the path coefficients after the model has been run (Hair et al., 2014). The strength of the linkages between the study constructs in the structural model is measured using path coefficients. The coefficients measure the strength of a link, with values around 1 indicating a strong positive link (Hair et al., 2014). Through the process of bootstrapping, the significance of the path is determined using t-statistics (Kock, 2014). The path coefficients and their significance levels show that the model is internally consistent (Hair et al., 2011). The route coefficients must be significant to assure the quality of the inner model (Wong, 2016). The study's path coefficients are shown in Table 5 below.

Table 5 - Path coefficients

Effect	Relationship	Path Coefficient
Direct	ES -> DC	0.322
	SP -> DC	0.170
	KC -> DC	0.295
	CU -> DC	0.070
	FO -> DC	0.494
Indirect / mediation	ES -> OLC-> DC	0.041
	SP -> OLC-> DC	0.297
	KC -> OLC-> DC	0.031
	CU -> OLC-> DC	0.202
	FO -> OLC-> DC	0.219

According to table 5, all path values of direct and direct effect are between 0.070 and 0.494, which supports the significance of the research hypotheses. Hence, the model shows that the Environmental scanning, Scenario planning, Knowledge creation, Culture, and Formal organization have a direct impact on Dynamic capabilities. Also, Organizational learning has an indirect effect on the relationship between Strategic foresight dimensions and Dynamic capabilities in the context of the public organisations in the UAE. The structural model's quality is further assessed in the subsections that follow.

5.2 Coefficient of determination (R2) assessment

R^2, which is a measure of the structural model's quality, is used to determine how much variation is explained by the model. R^2, also known as the coefficient of determination, is the total contribution of exogenous constructs in explaining or predicting the variance of the endogenous construct in the structural model. The higher the quality of a model, the more its variation can be explained/predicted, and vice versa (Hair et al., 2011; Hair et al., 2014; Wong, 2016). Despite the lack of uniform criteria for establishing how much R^2 is acceptable, several researchers have given recommendations for what should be considered reasonable, which vary by discipline. R^2 values of 0.25, 0.50, and 0.75, for example, are considered low, moderate, and substantial, respectively (Hair et al., 2014; Wong, 2016). In the consumer behaviour field, however, an R^2 value of 0.2 is considered high, according to Hair et al. (2014). Using these guidelines, the study's R^2 levels were determined. In table 6, the R^2s of the final model are listed.

Table 6 - R2 evaluation

Construct	R Square
Endogenous: Dynamic Capabilities	0.810
Mediator: Organizational Learning Capability	0.697

The research structural model's coefficients of determination (R^2) are shown in Table 6. Dynamic Capabilities has the value of 0.810, and Organizational Learning Capability has the value of 0.697 for the main endogenous constructs. The R^2 of the primary endogenous constructions is all above 0.5, as evidenced by the preceding. This indicates that the numbers are above average, implying that the models have a high level of prediction accuracy (Hair et al., 2014).

5.3 Predictive relevance (Q2) assessment

The structural model's predictive importance is examined using cross-validated redundancy. The data points of all indicators in the outer model of endogenous constructs were tested using Stone-predictive Geisser's relevance (Q^2) to see if they could be effectively predicted (Wong, 2016). The sample re-use methodology is used in this method, in which a section of the data matrix is omitted, model parameters are estimated, and the omitted portion is forecasted using the estimates (Hair et al., 2011; Hair et al., 2014). This quality evaluation criterion requires the cross-validated redundancy (Q^2) value to be a positive integer greater than 0 to have effective predictive relevance (Chin, 1998).

The study's final models are tested using the blindfolding technique and Smart-PLS software to calculate cross-validated redundancy (Q^2) using the aforementioned submission (Ringle et al., 2015). Table 7 displays the results of the blindfolding approach.

Table 7 - Predictive relevance

Constructs	SSO	SSE	Q^2 (=1-SSE/SSO)
Culture	92.734	92.734	
Dynamic Capabilities	394.078	226.796	0.424
Environmental Scanning	126.107	126.107	
Formal Organization	122.894	122.894	
Knowledge Creation	124.261	124.261	
Organizational Learning Capability	234.951	161.401	0.313
Scenario Planning	128.528	128.528	

• *According to Fornell and Cha (1994) a cv-red value of Q^2>0*

Table 7 shows the structural model's cross-validated redundancy. All endogenous constructs have Q^2 values greater than 0. This indicated that the study model was really useful in terms of forecasting (Chin, 1998).

5.4 Goodness-of-fit (GoF) assessment

PLS-SEM lacks a generally acknowledged global goodness of fit metric, unlike covariance-based structural equation modelling (Vinzi et al., 2010). Tenenhaus et al. (2004) proposed the "GoF" index as shown in equation (4.2) as a global goodness of fit criterion in an attempt to tackle this challenge. The index is made up of the geometric mean of the average communality index (AVE) and the average coefficient of determination (R^2). The following formula can be used to determine it:

$$GoF = \sqrt{\overline{AVE2}\ X\ \overline{R2}} \tag{4.2}$$

The GoF index aims to explain the PLS model's performance at both the measurement and structural levels, with an emphasis on the model's overall prediction performance (Memon and Rahman, 2013). The structural model is represented by R^2, while the quality of the index's measurement models is addressed by AVE^2. The GoF index of 0.1, 0.25, or 0.36 corresponds to tiny, medium, or large, respectively (Akter et al., 2011). The calculated model's GoF was 0.8423. The GoF of the research models is rated as high, according to Akter et al. (2011), indicating that the research models are of good quality.

5.5 Hypotheses testing

Hypothesis testing is conducted using bootstrapping function of SmartPLS software on the final model that has achieved measurement model fitness criteria. Figure 1 exhibit the final structural model after bootstrapping. The structural model and associated data are presented in Figure 2 is utilised to test the hypotheses of the study.

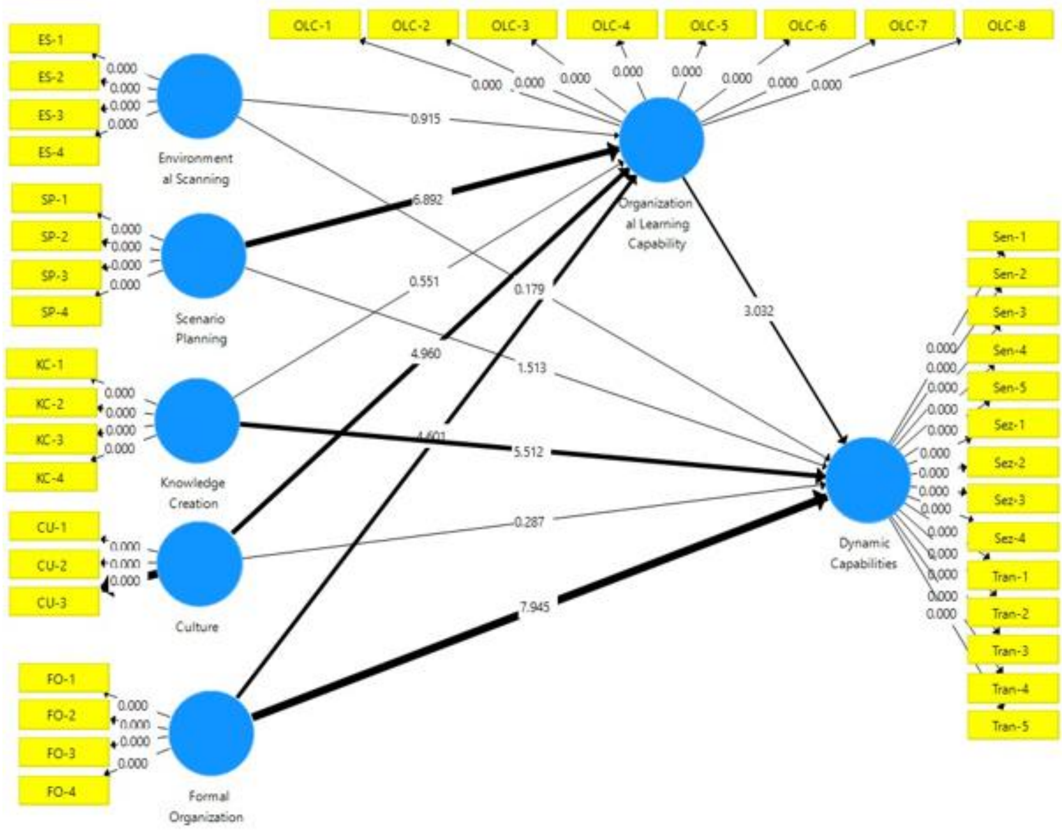

Fig. 2 - Final model after bootstrapping

The results of bootstrapping for hypothesis testing of **direct effect** relationship of the strategic foresight dimensions on dynamic capabilities of public organizations in the context of the UAE are shown in Table 8.

Table 8 - Results of direct effect relationship

Hypothesis	Direct effect relationships	Path strength	T Statistics (≥1.96)	Findings
H1	ES -> DC	0.322	0.179	**Not Supported**
H2	SP -> DC	0.170	1.513	**Not Supported**
H3	KC -> DC	0.295	5.512	Supported
H4	CU -> DC	0.070	0.287	**Not Supported**
H5	FO -> DC	0.494	7.945	Supported

Based on table 8, three of the relationships are not significant which are environmental scanning, scenario planning and culture dimensions toward the dynamic capabilities of organisation in UAE. only two of the relationships are significant which are knowledge creation has direct effect significant on dynamic capabilities and formal organisation has direct effect significant on dynamic capabilities.

The following is mediating effect or indirect effect of organizational learning capability on the relationship between the independent variables of strategic foresight dimensions and the dynamic capabilities of the organization. The mediator refers to a variable that account for all or part of the relationship between a predictor and outcome (Hair et al., 2014). The results of the indirect effect of Organization learning capability between the five independent variables – Environmental scanning, Scenario planning, Knowledge creation, culture, and Formal organization – and the dependent variable, namely Dynamic capabilities are as in table 9.

Table 9: Results of indirect/mediation effect relationship

Hypothesis	Indirect effect relationships	Path strength	T Statistics (≥1.96)	Findings
H6	ES -> OLC-> DC	0.041	0.923	Not Supported
H7	SP -> OLC-> DC	0.297	6.741	Supported
H8	KC -> OLC-> DC	0.031	0.656	Not Supported
H9	CU -> OLC-> DC	0.202	4.655	Supported
H10	FO -> OLC-> DC	0.219	4.774	Supported

Results from table 9, indicates that organizational learning capability has no mediation effects to environmental scanning and knowledge creation of the strategic foresight dimensions. However, the organizational learning capability has significant mediation effect to the relationships of scenario planning with dynamic capabilities, culture with dynamic capabilities and formal organisation with dynamic capabilities.

6. Summary

This study has developed and evaluated the SEM-PLS mediation model in SmartPLS software. The model which comprises of five exogenous constructs of strategic foresight dimensions; one endogenous construct of dynamic capabilities and one mediator construct of organisational learning capability of UAE organisations. The model was evaluated at measurement and structural components to achieve the fitness criteria values. It was found that the model has achieved GoF value of 0.8423 which indicates high overall validating power. This means that the model is rated as a high-quality model. After achieving these fitness criteria, hypothesis testing was conducted through bootstrapping function of the software. It was found that only two out of five of the direct effect relationships are significant, which are knowledge creation and formal organisation have significant relationships with the dynamic capabilities of the organisations. For mediation/indirect effect, it was found that organisational learning capacity as the mediator has significant effects toward three relationships which are scenario planning with dynamic capabilities; culture with dynamic capabilities and formal organisation with dynamic capabilities.

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