CHAPTER

2 Literature Review of Demand Models and Inventory Models for technology generation products

The evolution of technology generations in the wake of technological disruption has been elaborated in the last chapter, and it has also been noted how the nature of demand substitution in technology generations is different from that of the functional products, with the implications on the supply chain challenges. The Research Problem and Research Objectives have also been laid down. In this chapter[3], a detailed literature review of the inventory models shall be conducted for non-constant demand, for multiple item scenarios, and substitutable items. The studies that have dealt with innovation diffusion dependent demand and multiple technology generations shall also be studied. But before starting with the review of the inventory literature on these topics, this chapter shall have a glance at the existing literature on the innovation diffusion models to set the context of how demand behaves in the case of technology products. Therefore, this review starts with the assumptions of the basic EOQ model, and then relaxes those assumptions one by one, to see the literature of inventory modeling around those assumptions.

[3] This chapter is based on the following papers:

1. Nagpal, G. & Chanda, U. (2020). "Adoption and Diffusion of Hi-Technology Product and Related Inventory Policies - An Integrative Literature Review", *International Journal of e-Adoption,* Published in April 2020.
2. Nagpal, G. & Chanda, U. (2020). "Review of Innovation Modeling Literature", *Transforming Management using Artificial Intelligence techniques,* Edited by Garg, V. and Agrawal, R., CRC Press, 157-168.
3. Nagpal, G. & Chanda, U. (2021). "The Five Decades of Modelling for Substitutable Products: A Comprehensive Literature Review", *Operations and Supply Chain Management: An International Journal,* Accepted for publication
4. Nagpal, G. & Chanda, U. (2021). "Use cases of Innovation Diffusion and Adoption Theories in diverse industries: A Literature Review", *International Journal of e-Adoption* (Under Review)

The first EOQ Model was introduced by Harris in 1913. It was published in Factory, the Magazine of Management under the title "How many parts to make at once" (Harris, 1913). Since then, drastic research work has happened in this area. Something that started from a short document of 2.25 pages by Harris has now been expanded to millions or billions of pages by the following researchers. It is the beauty of Harris' Model in terms of its simplicity that has made it a fundamental model in the area of inventory optimization. The primary emphasis of his model has been to show the trade-off between inventory ordering and inventory carrying cost. Undoubtedly, Harris can be very well called as the Father of Inventory Management Theory. The term "lot size" when searched for in Google Scholar results in 3.63 million results, while the term "Economic Order Quantity" results in 2.74 million results, indicating the popularity of the research work on inventory models. Even the reprints of the Harris model (i.e. Erlenkotter, 1989 and Erlenkotter, 1990) published in 1989 and 1990 have been highly cited in the literature.

2.1. Assumptions of the basic EOQ Model:

Assumption 1: Demand rate of the product is constant
Assumption 2: There is only one item in the supply chain
Assumption 3: There is no demand substitution from other items
Assumption 4: The influence of the trade credits on the demand or the inventory costs is ignored
Assumption 5: There is unlimited warehousing space available
Assumption 6: The selling price of the product is constant, and the inflation effect is ignored
Assumption 7: All the business parameters are deterministic and precise
This chapter shall relax the assumptions mentioned above one by one and review the literature around the same.

2.2. Review Methodology

The extensive search of the literature was carried out on the popular research databases: Springer, Wiley, Scopus, Science Direct, Jstor, Absco, Web of Science. Although this review does not claim to be an exhaustive one, the attempt has been made to cover all the possible aspects of diffusion modeling that have been worked upon. After the first search of the studies using the keywords, the studies found were screened to filter out the irrelevant studies. For eg: the word diffusion modeling also yielded many studies on chemistry for the diffusion of chemicals in the solvents, which were not relevant to our theme. After the irrelevant studies were screened out, the citation chaining was done on the shortlisted studies to search for more studies relevant to our theme. Also, the snowballing technique was used to refresh the list of the keywords obtained from the newly discovered studies. The backward chaining of the references was also done to help in accessing more studies.

To ensure the quality, this study covers the review of the research studies mostly published in reputed Scopus-indexed or ABDC rated journals. The study discovers that the research that has been done on the inventory optimization of multi-generation technology products is not only rare but also very restrictive in its scope and assumptions. The study then proposes directions for future research.

2.3. Review of the inventory models on non-constant demand

This section explains how the different inventory models have expanded the work of Harris to the non-constant demand rates of diverse types. It sheds light on the nature of demand considered in the different research studies on inventory modeling. Juneau & Coats (2001) argued that the underlying of a product evolves and suggested an exponential time demand function for optimal EOQ policies. Chern et al. (2001) discussed EOQ models considering a demand rate influenced by promotion decisions. Pramanik et al (2017) argued in favor of considering the effect of promotional effort strategy on EOQ policies. Sundararajan et al (2019) discussed inventory policies by considering price elasticity driven demand function. Chanda and Kumar (2011) suggested that innovation diffusion models can be one of the ways to capture the effect of life cycle dynamics on inventory policies for technology products. Based on the nature of the problem, researchers have considered different forms demand function to formulate optimal inventory policies such as constant demand (Bhunia et al. 2014, Chang et al. 2010, Chen and Kang 2010, Feng et al. 2013, Mahata 2012), price-dependent demand (Kim et al. 1995, Kwak and Kim 2017, Lu et al. 2016, Molamohamadi et al. 2014, Neda et al. 2016), stock dependent demand (Sarkar 2012, Singh and Sharma 2014, Pal and Chandra 2014, Min et al. 2010), credit dependent demand (Annadurai and Uthayakumar 2013, Chern et al. 2013, Chung 2012b, He and Huang 2013, Wang et al. 2014), time dependent demand (Arkan and Hejazi 2012, Chakraborty et al. 2013, Chanda and Kumar, 2011, Chanda and Kumar, 2017), stochastic demand (Arkan and Hejazi 2012, Chakraborty et al. 2013), innovation diffusion governed demand (Chanda and Kumar, 2011, Chanda and Agarwal, 2014, Chanda and Kumar, 2017, Chanda and Kumar, 2019), etc.

From Table2.1, it can be observed that varied types of demand rate functions were used in inventory literature to imitate the business model of a firm.

Table2.1. Demand rate function of some of the popular inventory studies

Author (Year)	A	B	C	D	E	F	G
Alfares and Ghaithan (2016)	☐	✓	☐	☐	☐	☐	☐
Annadurai and Uthayakumar (2013)	☐	☐	☐	☐	✓	☐	☐
Arkan and Hejazi (2012)	☐	☐	☐	☐	☐	✓	☐
Bhunia et al. (2014)	✓	☐	☐	☐	☐	☐	☐
Chakraborty et al. (2013)	☐	✓	☐	☐	☐	✓	☐
Chanda and Kumar (2011)	☐	☐	✓	☐	☐	☐	☐
Chanda and Agarwal (2014)	☐	☐	✓	☐	☐	☐	✓
Chanda and Kumar (2017)	☐	☐	✓	☐	✓	☐	☐
Chanda and Kumar (2019)	☐	☐	✓	☐	✓	☐	☐
Chang et al. (2010)	☐	☐	☐	✓	☐	☐	☐
Chang et al. (2010)	✓	☐	☐	☐	☐	☐	☐
Chang et al. (2010)	✓	☐	☐	☐	☐	☐	☐
Chen and Kang (2010)	✓	☐	☐	☐	☐	☐	☐
Chen and Xiao (2017)	☐	✓	☐	☐	☐	☐	☐
Chen et al. (2013)	✓	☐	☐	☐	☐	☐	☐
Chen et al. (2015).	☐	☐	☐	☐	☐	✓	✓
Chen et al. (2017)	☐	✓	☐	☐	☐	☐	☐
Cheng et al. (2012)	✓	☐	☐	☐	☐	☐	☐
Chern et al. (2013)	☐	☐	☐	☐	✓	☐	☐
Chern et al. (2014)	☐	☐	☐	☐	✓	☐	☐
Chuang et al. (2013)	✓	☐	☐	☐	☐	☐	☐
Chung (2010)	✓	☐	☐	☐	☐	☐	☐
Chung (2011)	✓	☐	☐	☐	☐	☐	☐
Chung (2012a)	✓	☐	☐	☐	☐	☐	☐
Chung (2012b)	☐	☐	☐	☐	✓	☐	☐
Chung (2013)	✓	☐	☐	☐	☐	☐	☐
Chung and Lin (2011)	✓	☐	☐	☐	☐	☐	☐
Chung et al. (2013)	✓	☐	☐	☐	☐	☐	☐
Dye and Yang (2016)	☐	✓	☐	☐	☐	☐	☐
Feng et al. (2013)	✓	☐	☐	☐	☐	☐	☐
Feng et al. (2015)	☐	✓	☐	☐	☐	☐	☐
He and Huang (2013)	☐	☐	☐	☐	✓	☐	☐
Herbon & Khmelnitsk (2017)	☐	✓	☐	☐	☐	☐	☐
Hu and Liu (2010)	✓	☐	☐	☐	☐	☐	☐
Huang et al. (2013)	✓	☐	☐	☐	☐	☐	☐
Jaggi and Verma (2010)	✓	☐	☐	☐	☐	☐	☐
Kar et al. (2001)	☐	✓	☐	☐	☐	☐	☐
Ke et al (2013)	☐	☐	✓	☐	✓	☐	✓
Khanna et al. (2017)	☐	✓	☐	☐	☐	☐	☐
Kim et al. (1995)	☐	✓	☐	☐	☐	☐	☐

Kreng and Tan (2010)	✓	□	□	□	□	□	□
Kreng and Tan (2011)	✓	□	□	□	□	□	□
Kumar and Chanda (2018)	□	□	✓	□	□	□	□
Kwak & Kim (2017)	□	✓	□	□	□	□	□
Li et al. (2014)	✓	□	□	□	□	□	□
Liang and Zhou (2011)	✓	□	□	□	□	□	□
Liao and Huang (2010)	✓	□	□	□	□	□	□
Liao et al. (2012)	✓	□	□	□	□	□	□
Liao et al. (2013)	✓	□	□	□	□	□	□
Liao et al. (2013)	✓	□	□	□	□	□	□
Liao et al. (2014)	✓	□	□	□	□	□	□
Lin et al. (2012)	□	□	□	□	✓	□	□
Lin et al. (2016)	□	✓	□	□	□	□	□
Liu et al. (2015)	□	✓	□	□	□	□	□
Liuxin at al. (2018)	□	✓	□	✓	□	□	□
Lu et al. (2016)	□	✓	□	□	□	□	□
Mahata (2012)	✓	□	□	□	□	□	□
Mahajan and Van Ryzin (2001).	□	□	□	□	□	✓	✓
Mahmoodi (2016)	□	✓	□	□	□	□	□
Min et al. (2010)	□	□	□	✓	□	□	□
Molamohamadi et al. (2014)	□	✓	□	□	□	□	□
Moussawi-Haidar et al. (2014)	✓	□	□	□	□	□	□
Musa and Sani (2012)	✓	□	□	□	□	□	□
Nagarajan and Rajagopalan, (2008)	□	□	✓	□	□	✓	✓
Neda et al. (2016)	□	✓	□	□	□	□	□
Ouyang and Chang (2013)	✓	□	□	□	□	□	□
Pal and Chandra (2014)	□	□	□	✓	□	□	□
Palanivel et al. (2016)	□	□	□	✓	□	□	□
Paul et al. (2014)	□	✓	□	□	□	□	□
Pasternack and Drezner (1991)	□	✓	□	□	□	✓	✓
Qin et al. (2014)	□	✓	□	□	□	□	□
Rabbani et al. (2016)	□	✓	□	□	□	□	□
Roy and Samanta (2011)	✓	□	□	□	□	□	□
Sarkar (2012)	□	□	□	✓	□	□	□
Singh and Sharma (2014)	□	□	□	✓	□	□	□
Soni (2013)	□	□	□	✓	□	□	□
Su (2012)	✓	□	□	□	□	□	□
Taleizadeh et al. (2013)	✓	□	□	□	□	□	□
Teng and Lou (2012)	□	□	□	□	✓	□	□
Teng et al. (2011)	□	□	□	✓	□	□	□
Teng et al. (2012)	✓	□	□	□	□	□	□

Thangam (2012)	✓	☐	☐	☐	☐	☐	☐
Tsao (2011)	✓	☐	☐	☐	☐	☐	☐
Tung et al. (2014)	✓	☐	☐	☐	☐	☐	☐
Uthayakumar and Priyan (2013)	✓	☐	☐	☐	☐	☐	☐
Wang et al. (2014)	☐	☐	☐	☐	✓	☐	☐
Yang (2010)	✓	☐	☐	☐	☐	☐	☐
Yang and Chang (2013)	✓	☐	☐	☐	☐	☐	☐
Zhong and Zhou (2012)	✓	☐	☐	☐	☐	☐	☐
Zhong and Zhou (2013)	☐	☐	☐	✓	☐	☐	☐

A: Constant demand, B: Price-dependent demand; C: Innovation diffusion governed demand; D: Stock dependent demand, E: Credit dependent demand, F: Stochastic demand; G: Substitution effect

2.3.1. Review of Diffusion Modelling for Innovations

As discussed earlier, when a technology product gets introduced in the market, the first set of customers to adopt them are the ones who have the willingness to try something new and are often termed as early adopters. Such category of customers do not need any word of mouth feedback but get converted by the advertising itself. The customers who adopt the product in the later stages of the product life cycle are increasingly averse to trying new products, and are thus, more influenced by the imitation effect rather than the innovation effect. Thus, it can be observed that the innovation effect and imitation effect both play an important role in the diffusion of technology products. Many researchers have come out with robust models for the demand for innovative products.

The origins of diffusion modeling can be traced back to the early 20th century when Schumpeter created the innovation theory and studied the imitation behavior between individuals. Mansfield (1961) introduced the concept of technological change and the role of imitation in the same. Rogers (1962) proposed that diffusion comprises of innovation, communication channels, time, and space. He also came up with the theory of innovation diffusions, which was the first insightful and revolutionary work on the innovation diffusions. He defined *diffusion of innovation* as the process through which an innovation is accepted among the members in a social system over time. Rogers (1965) explained how a product or an idea gains momentum and gets diffused through a population. In particular, the most popular and widely cited works on innovation diffusion are by Bass (1969) that assumed the demand rate is governed by the hazard rate function. This has been widely accepted due to the simplicity of the approach and the applicability to real-life scenarios.

As early as in the 1970s, Fisher and Pry (1971), Blackman (1975), and Bretschneider & Mahajan (1980) modeled the technological substitution. One of the earliest works on dynamic pricing for new product launches by Robinson and Lakhani (1975). Fisher and Pry (1971) first proposed the technological substitution models for two-generation products. Rogers (1971) said that the adoption of the new products follows a bell-shaped distribution over time and that the innovativeness of a customer influences his adoption timing of a product. Later on, many extensions of the model were from different dimensions (Blackman, 1974; Stern et al., 1975; Bretschneider and Mahajan, 1980; Kamakura and Balasubramanian, 1987).

As discussed in the paragraph above, different individuals in a social system adopt innovation at different points of time. They can be categorized into broad categories based on innovativeness, i.e. their tendency to adopt an innovation earlier than the other members of the social system (Rogers, 1983). While the early adopters are more prone to taking risks and more socially networked, the laggards are very risk-averse and generally less networked. The early adopters are the first ones to adopt an innovation, followed by the early majority adopters who deliberate a little before taking an adoption decision but are willing to adopt it. The late majority are characterized by skepticism and wait for the other members to adopt an innovation before they take a plunge. Laggards are very dogmatic and fixated to the long-existing traditions and hence, the latest ones to adopt the innovations.

Figure2.1 shows that the initial sales of the product are attributed to the innovators, while the latter portion of sales is attributed to the laggards, with the cumulative adoption following the S-shaped curve, also known as Fourt and Woodlock Curve.

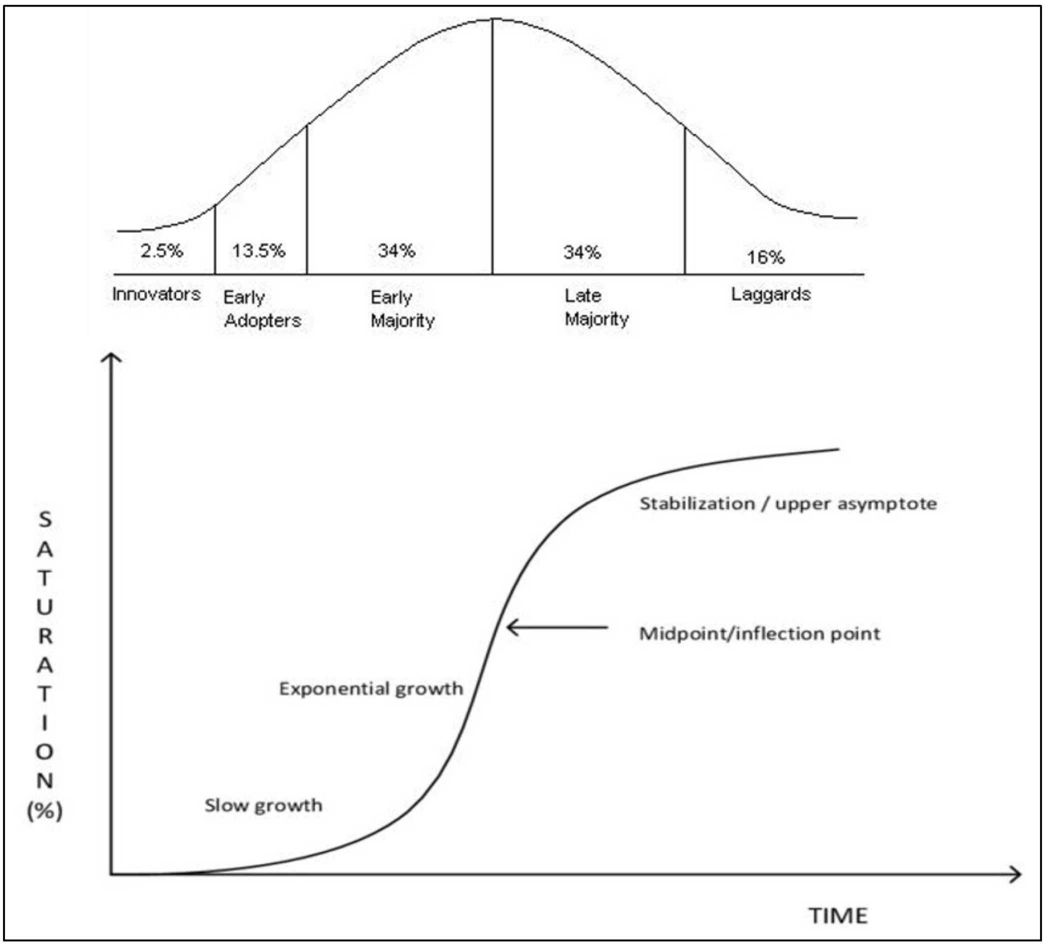

Figure2.1. The product life cycle of innovations and the cumulative adoption illustrated by the S-shaped curve

Attitude is a major determinant of behavior. (Fishbein, 1967; Fishbein, 1968; Fishbein and Ajzen, 1974). Ajzen (1985) said that human behavior is generally well-planned and designed in advance, although the execution occurs as the plan unfolds. This came to be called the Theory of Planned Behaviour and influences the way the adopters adopt the innovation. Davis (1989) proposed the Technology Acceptance Model (TAM) to explain the behavioral intention of a potential adopter to adopt an innovation. The TAM was later validated to be a robust model by King and He (2006).

Bass (1980) suggested that the diffusion rates are also dependent upon the price elasticity of demand and the learning curve of the potential adopters. Dolan and Jeuland (1981) also used the experience curve of the consumers to formulate the dynamic demand models. Jeuland and Dolan (1982) emphasized how dynamic pricing can play an important role in new product planning. Schmittlein and Mahajan (1982) used the maximum likelihood method to estimate the diffusion models. Horsky and Simon (1983) had studied the influence of advertising on the diffusion of innovations. Kalish (1985) added the effect of price and advertising along with uncertainty. Winer (1985) came up with the price vector model of demand for consumer durables and studied how price influences the choice of consumers in the process of purchasing consumer durables by proposing a vector of five price concepts. Mahajan et al. (1986) assessed various estimation procedures for new product diffusion. Srinivasan and Mason (1986) minimized the sum of squares of deviations from non-linear relationships to estimate the new product acceptance. Kamakura and Balasubramanian (1987) incorporated the factor of repeat purchase, price index, and population change dynamics. Later on, Norton and Bass (1987) extended the framework to capture the demand dynamics of substitutable technology generation products. This study advocated that the new generation product will completely cannibalize the sales of old generation products over some time. Bulte and Lilien (1997) showed that all the three methods of parameter estimation- Ordinary Least Squares Estimation, Maximum Likelihood Estimation, and Non-linear least squares estimation, are subject to bias. Levin (1987) said that the market structure in a particular industry is a strong determinant of the innovation adoption rate in the beginning stages while its role diminishes in the later stages. Lieberman and Montgomery (1988) said that leadership in product and process technology can lead to first-mover advantages for a firm and so, the adoption of innovations becomes very important in this context. Kamakura et al. (1988) used nested models to test the role of price and influence in innovation diffusion. Meade and Islam (1988) worked on combining models for innovation diffusion, realizing the fact that one pure model cannot forecast technological growth. Dockner and Jorgensen (1988) came up with optimal advertising policies for product diffusion. A few of the useful works in the 1980s can be attributed to Easingwood (Easingwood et al., 1981; Easingwood et al., 1983; Easingwood, 1987; Easingwood, 1988).

Many of the researchers have done empirical research in various domains to understand the adoption behavior of the customer in different nations of the World. The Table2.2 lists down a few of such studies.

Table2.2. The research studies that have studied consumer behavior using different theories of innovation adoption

Work	Use Case	Country of Research
Yuen et al. (2020)	Autonomous Vehicles	S. Korea
Yoon et al. (2020)	Tech-savvy Agriculture	S. Korea
Zhang et al. (2020)	Car-washing system	Japan
Li et al. (2020)	Eco-friendly commuting patterns	China
Ng (2020)	Social Networking	US
Brand et al. (2020)	Grocery shopping	UK
Albayati et al. (2020)	Blockchain	S.Korea
Dayal & Palsapure (2020)	Online shopping	India
Chatterjee & Bolar (2019)	Mobile wallet	India
Talukder et al. (2019)	Wearable technology	China
AlRahmi et al. (2019)	MOOC Courses	Malaysia
Shao et al. (2019)	Online Payments	China
Phaosathianphan & Leelasantitham (2019)	Travel-Tech	Thailand
Gao et al. (2019)	bike-sharing	China
Min et al. (2019)	bike-sharing	US
Kamble et al. (2019)	blockchain	India
Gebert-Persson et al. (2019)	Online Insurance	Sweden
Shabanpour et al. (2018)	Autonomous Vehicles	US
Joia & Altieri (2018)	e-hailing apps	Brazil
Talebian & Mishra (2018)	Autonomous Vehicles	Iran
Ifinedo (2018)	Learning Blogs	Canada
Nieuwenhuijsen et al. (2018)	Autonomous Vehicles	Netherlands
Ismailova & Muhametjanova (2018)	E-governance websites	Kyrgyz Republic
Karahoca et al. (2018)	Health-tech	Turkey
Shukla & Sharma (2018)	Grocery Shopping	India
Kwon et al. (2017)	Health-tech	S. Korea
Hong et al. (2017)	Smartwatch	Taiwan
Cheng (2017)	Learning Blogs	Taiwan
Agarwal et al. (2017)	Multi-gen products	India
Pollock (2017)	Health-tech	US
Hsiao (2017)	Smartwatch	Taiwan
Hung et al. (2017)	Multi-gen products (DRAM processing technologies)	Taiwan
Widodo et al. (2017)	Online music products	Indonesia
Lou & Li (2017)	Blockchain	Taiwan
Wu et al. (2016)	Smartwatch	Taiwan
Joia et al. (2016)	Home brokerage systems	Brazil
Oliveira et al. (2016)	Online Payments	Portugal
Agag & ElMasry (2016)	Online travel products	UK
Li & Huang (2016)	Game-based learning	Taiwan
Shiau & Chau (2016)	Cloud computing classroom	Taiwan
Wang et al. (2016)	Hybrid electric vehicles	China

Soon et al. (2016)	Big data	Malaysia
Rice & Pearce (2015)	Mobile phone adoption	US
Kapoor et al. (2015)	IRCTC Mobile ticketing service	India
Zollet & Back (2015)	Interactivity innovations on corporate websites	Switzerland and Germany
Alsaad et al. (2015)	B2B E-Commerce	Malaysia
Zsifkovits & Gunther (2015)	Multi-gen products (Fuel cell vehicles)	Austria
Abroud et al. (2015)	Online trading	Iran
LawsonBody et al. (2014)	E-governance websites	US
Dash et al. (2014)	Mobile Banking	India
Hsu et al. (2014)	Cloud computing	Taiwan
Pham & Anh (2014)	e-banking	Vietnam
Smith et al. (2014)	e-ticketing for entertainment	US
Ramayah et al. (2014)	Online trading	Malaysia
Kreng and Jyun (2013)	Multi-gen products (golf club services)	Taiwan
Tsai et al. (2013)	RFID adoption by suppliers	Taiwan
Hameed et al. (2012)	IT innovation adoption in organizations	UK
Liu et al. (2012)	Online trading	Taiwan
Lee et al. (2011)	e-learning systems	Taiwan
Peres et al. (2011)	Mobile electronic tourist guides	Portugal
Mesak et al. (2011)	Subscriber service innovations	US
Lin (2011)	Mobile banking	Taiwan
Tsai et al. (2010)	RFID adoption by retail chains	Taiwan
Duan et al. (2010)	e-learning systems	China
Oh et al. (2009)	Online trading	S. Korea
Lean et al. (2009)	E-governance websites	Malaysia
Lee (2009)	Online trading	Taiwan
Tong (2009)	Online recruitment	Malaysia
Lin et al. (2007)	Online gaming	Taiwan
Tung & Chang (2007)	Online learning	Taiwan
Tseng (2007)	Travel	Taiwan
Kamarulzaman (2007)	e-commerce	UK
He et al. (2006)	Online payments	China
Azab (2005)	Online recruitment	Egypt
Gharavi et al. (2004)	IT in the stockbroking industry	Australia
Hsu & Lu (2004)	Online gaming	Taiwan
Rajagopal (2002)	ERP systems adoption	India
Assimakopoulos (2000)	GIS innovations	UK
Agarwal & Prasad (2000)	Software process innovations	India
Dooley (1999)	Educational technologies	US
Sgobbi (1995)	Robotics in services	Italy

Amey (1995)	Engine management technologies	US
Speece & Maclachlan (1985)	Multiple generations of Technology	US

As shown in Table2.2, innovation adoption theories have been applied to a multitude of technological innovations. The most popular areas of used-cases belong are autonomous vehicles, smartwatches, e-learning. Online payments, mobile apps, health-tech, IT-enabled services, e-governance, blogs, RFID adoption, and multi-generation products among others. The largest number of published use-cases belong to Taiwan accounting for 19 out of 86 published studies, followed by the US, China, and Malaysia.

While the theory of Diffusion of Innovations has been the most popularly used one in the research studies, there are certain other theories on the adoption of technology such as TAM (Technology Acceptance Model), TOE (Technology, Organization, and Environment) Model, TPB (Theory of Planned Behaviour), UATUT (Unified Acceptance Theory and), etc. The Table2.3 lists down a few of the studies that have used these theories.

Table2.3. The diffusion theories used in the different research studies

Diffusion Model or Theory	Research work(s)
Diffusion of Innovations (Proposed by Rogers in 1962)	Yuen et al. (2020); Yoon et al. (2020); Zhang et al. (2020); Li et al. (2020); Ng (2020); Chatterjee & Bolar (2019); Talukder et al. (2019); AlRahmi et al. (2019); Shao et al. (2019); Shabanpour et al. (2018); Joia & Altieri (2018); Talebian & Mishra (2018); Ifinedo (2018); Nieuwenhuijsen et al. (2018); Ismailova & Muhametjanova (2018); Karahoca et al. (2018); Kwon et al. (2017); Hong et al. (2017); Cheng (2017); Agarwal et al. (2017); Pollock (2017); Hsiao (2017); Wu et al. (2016); Joia et al. (2016); Oliveira et al. (2016); Agag & ElMasry (2016); Li & Huang (2016); Shiau & Chau (2016); Wang et al. (2016); Rice & Pearce (2015); Kapoor et al. (2015); Alsaad et al. (2015); Lawson-Body et al. (2014)
Technology Organization and Environment Model Tornatzky and Fleischer in 1990)	Yoon et al. (2020); Joia & Altieri (2018); Kapoor et al. (2015)
Technology Acceptance Model (Proposed by Davis and Bagozzi in 1989)	Chatterjee & Bolar (2019); AlRahmi et al. (2019); Joia & Altieri (2018); Ifinedo (2018); Ismailova & Muhametjanova (2018); Karahoca et al. (2018); Hong et al. (2017); Wu et al. (2016); Oliveira et al. (2016); Agag & ElMasry (2016); Shiau & Chau (2016); Peres et al. (2011); Oh et al. (2009)
Multi-generational Diffusion Models	Kreng & Jyun (2013); Zsifkovits & Gunther (2015); Hung et al. (2017); Speece & Maclachlan (1995); Agarwal et al. (2017)
Expectation Confirmation Model (Bhattacherjee in 2001)	Ifinedo (2018); Hong et al. (2017)
Theory of Planned Behaviour (Proposed by Ajzen in 1985)	Chatterjee & Bolar (2019); Shiau & Chau (2016); Wang et al. (2016)
UTAUT (Unified Theory of Acceptance and Use of Technology, Proposed by Venkatesh in 2003)	Talukder et al. (2019); Ismailova & Muhametjanova (2018); Wu et al. (2016); Oliveira et al. (2016)
Trustworthiness Model (proposed by Stephen Marsh in 1994)	Chatterjee & Bolar (2019); Shao et al. (2019); Ismailova & Muhametjanova (2018)
Task Technology Fit Model (proposed by Goodhue & Thompson, 1995)	Hsiao (2017)
Agent-Based Model (proposed by von Neumann in the 1960s)	Talebian & Mishra (2018)
Hierarchial Control Model	Alsaad et al. (2015)
Social Cognitive Theory	Ifinedo (2018)
Digital Divide Model	Rice & Pearce (2015); Lawson-Body et al. (2020)
Motivational Model	Shiau & Chau (2016)
Social Network Theory	Cheng (2017)
Perceived enjoyment Theory	Wu et al. (2016)

Perceived Characteristics of Innovation Theory	Kapoor et al. (2015)
Extended TPB with moral principles	Wang et al. (2016)
Perceived Desirability Theory	Alsaad et al. (2015)

From Table2.3, it becomes explicit that Roger's Theory of Diffusion of Innovations has been most widely used, followed by the TAM. Also, it is noteworthy to note that most of the studies have used multiple theories only to take the relevant constructs from each one of them to create a unified model that is best for that scenario and is validated by the past data.

Figure2.2 shows the framework of three popular theories- TAM, UATUT, and TPB used in the literature. The techniques used for modeling range from simple regression to structural equation modeling, longitudinal studies, and partial least squares estimation among others. Also, all these studies contain empirical research with insights generated from the data collected from the respondents. While some have used a questionnaire, others have used the interviews for data collection, and a few studies have used the combination of them.

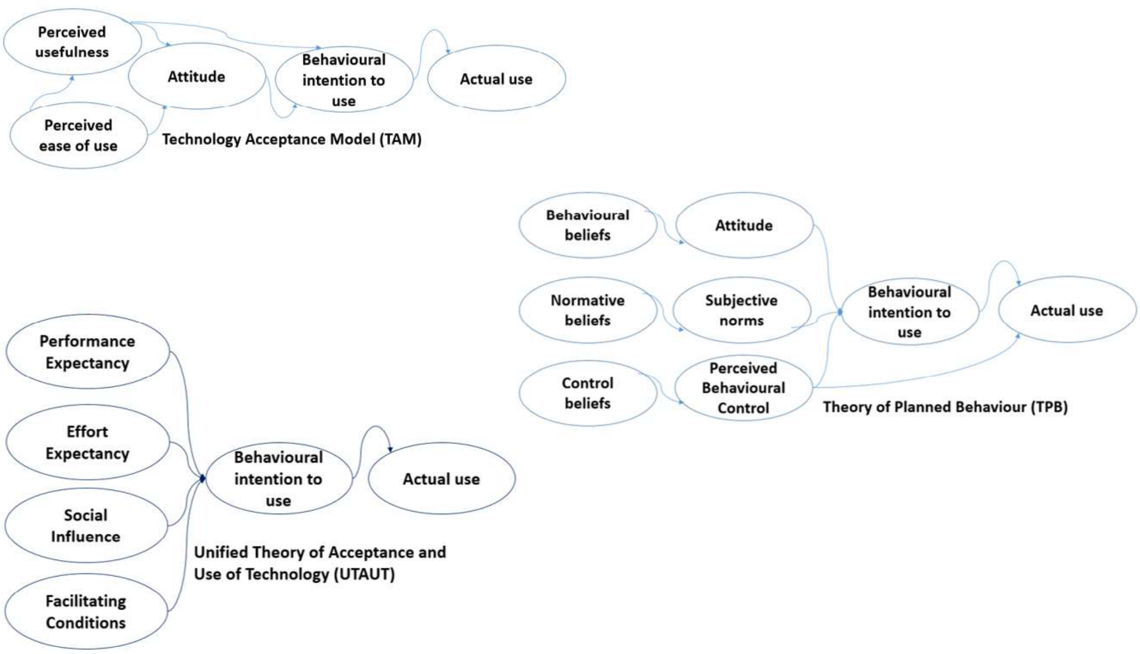

Figure2.2. The framework of three popular innovation adoption theories

Source: Composed by the author

Figure2.3 represents the important keywords used in the research articles that have been published on the used cases of innovation diffusion models in the visual format of a word cloud.

Figure2.3. Word Cloud of the keywords used in the research articles

The Figure2.4 taken from Norton and Bass (1987) shows how the successive generations in the case of technology products enjoy a higher market potential as well as a much faster diffusion rate as compared to the earlier generations.

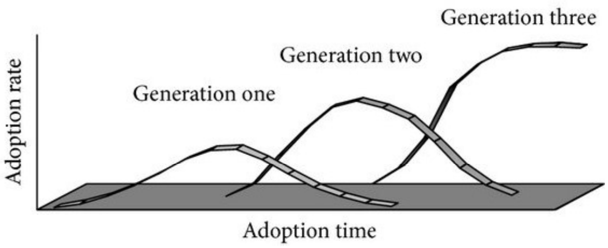

Figure2.4. The Series of Technology Generations
Source: Norton Bass Model (1987)

Multi-generation technological substitution models (Norton and Bass, 1987; Mahajan and Muller, 1996; Chanda and Bardhan 2008, Chanda and Das 2015) and optimization models that address issues such as market entry timing or pricing strategies for successive generations (Wilson and Norton, 1989; Lilien and Yoon, 1990; Bayus, 1992; Bayus; 1994, Mahajan and Muller, 1996; Kim et al. 2001) can also be considered to be part of this stream (Kim, Srivastava and Han 2001).

Horsky (1990) advocated the consumer income, product price, and information as the three key determinants of technological adoption; and suggested that the overall market potential is influenced by these three factors. Jain and Rao (1990) studied the effect of price elasticity of demand on consumer durables. Mahajan and Muller (1990) also performed an insightful review of diffusion modeling literature existing at that time. Lilien and Yoon (1990), and Mahajan and Muller (1996) worked upon the timing of the innovations. The demand for technology products follows the process of innovation diffusion (Speece & MacLachlan, 1992). To further add to this complexity of a highly non-linear demand pattern, multiple products are co-existing at the same time in the market. These different generations of products have an inter-play among themselves to influence the demand pattern which creates further stress for the supply chain. This type of substitution in which the consumers switch to another product due to its technological superiority is called technological substitution.

Smith (1992) delineated three types of technological substitution- functional, product, and asset. Bayus (1992) and Bayus (1994) stated that the product life cycles are getting compressed with the ever-evolving consumer preferences and with the advent of newer technologies. Bass et al. (1994) came up with an adaptation of his original diffusion model to incorporate the effect of the decision variables such as price, advertising spends, etc. Bridges et al. (1995) modeled the market share as a function of customer expectations. Speece and Maclachlan (1995) applied the innovation diffusion model to multiple generations of milk container technology. Putsis (1996) studied the influence of purchasing frequency in a temporal aggregation of innovation products' demand.

Littlejohn (1996) while explaining the expectancy-value theory proposed by Martin Fishbein also said that attitudes and beliefs have a substantial impact on the adoption timing of an innovation by an adopter. Azjen (1996) also emphasized the influence of social psychology on individual decision making, which holds good in the decisions to adopt innovation as well. Lefebre et al. (1996) while evaluating the factors affecting the innovativeness of 116 small manufacturing firms concluded that soft factors such as the technical skills of blue-collar workers, the motivation for process improvement, and the influence of customers and vendors strongly influence the technology adoption. Infante et al. (1997) said that opinion leaders and change agents enjoy significant influence over the adoption or rejection decisions of the individual potential adopters. Dekimpe et al. (1998) modeled the timing of adoption across the nations under globalization. Radas and Shugan (1998) formulated the model for optimal timing and seasonal marketing of new product launches. Krishnan et al. (1999) came out with an optimal pricing strategy for new products. Thong (1999) also said that the extent of innovation adoption is more influenced by the organizational characteristics, while the decision to adopt is more influenced by the innovation characteristics.

Bass et al. (2000) and Danaher et al. (2001) studied the impact of the marketing mix on the new product diffusion models. Pae and Lehmann (2003) studied the impact of inter-generational time on innovation diffusion. Frank et al. (2004) said that the implementation of an innovation is governed not only by the communication but also by the social pressure and informal access to expertise. Chanda and Bardhan (2008) came out with useful insights into the diffusion of technology generations. Stremersch (2010) showed that the growth rate of new products increases with the advancement of technology generations.

Waarts et al. (2002) proposed that the driving factors behind the innovation adoption are not the same at all periods, and said that factors behind early adoption may be significantly different from the factors behind late adoption. Putsis and Srinivasan (2000) developed the forecasting techniques for macro-level diffusion models. Kim et al. (2001) came up with a model that included initial and repeat purchases for multiple generations of innovative products and allowed for leapfrogging. Kim and Shin (2015) also suggested the influence of customer reviews on the products' sales. Lee et al. (2016) said that even the product preferences among technology products change with time.

Bass et al. (2000) and Danaher et al. (2001) modeled the technological substitution as a function of the overall marketing mix. Mahajan and Ryzin (2001) proposed the stochastic gradient algorithm for a single period stochastic inventory problem in which a sequence of heterogeneous consumers substitute among the product variants in a retail setup. Wejnert (2002) gave the conceptual framework for integrating the diffusion models that have been worked upon till then. Netessine and Rudy (2003) modeled the substitution by allowing the demand shortages to be covered by the other products and compared the two scenarios of centralized and competitive inventory management under substitution. Tajfel and Turner (2004) said that people get a feel of social belongingness and self-esteem from their memberships in groups and therefore, get influenced by the behaviors and attitudes of their groups towards the adoption of innovations. An important work that studied diffusion from the perspective of consumer psychology is that of Brown and Heathcote (2008). It is also worthwhile to note the work of Wajnara (2002), Young (2009), and Winer (2011) who studied the diffusion of innovations at the micro-level in contrast to the earlier macro-level models. Chanda and Bardhan (2008) illustrated that the later generations have a higher imitation effect but lesser innovation effect than the earlier generations. Grasman et al. (2009) analyzed the measures of central tendency and dispersion for the response times to estimate the parameters in diffusion models. Thompson et al. (2009) while examining the adoption of e-procurement among firms found that its adoption tendency is positively associated with the firm size, the top management support, the business partner influence, and the perceived benefits.

When it comes to an organization's adoption rate of new technologies or the pace of new product development, process and team characteristics are more important than the strategy and project characteristics of the firm (Chen et al. 2010). Stefan et al. (2010) suggested that the newer product launches witness higher growth as compared to the earlier ones. Arts et al. (2011) showed that the innovation characteristics have a different influence when it comes to adoption intention vis-à-vis the actual adoption behavior. While the potential adopters intend to adopt the innovations that are more complex and meet their needs better, but they adopt the ones that are less sophisticated and offer higher relative advantages. Vulcano et al. (2011) said that the primary demand of substitutable products can be estimated from the point of sales data. Vaagen et al. (2011) modeled consumer-directed substitution. Kuo and Huang (2012) worked on the optimal pricing for multi-generational products. Hung and Lai (2012) highlighted the non-linear behavior of demand when the older technologies are replaced by newer ones. Dutilh et al. (2013) modeled the diffusion as a function of the biological age of the adopter. Germar et al. (2014) suggested that social influence and perceptions have an important role to play in diffusions and modeled the same. Camison and Lopez (2014) said that organizational innovation has a positive influence on the development of technological innovation products and services, and therefore, on firm performance. Zhang et al. (2015) used the theory of innovation diffusion to study the factors influencing the acceptance of e-health innovations among the patients. Lerche and Voss (2016) suggested that diffusion models should be made more parsimonious. Sachdeva et al. (2016) developed a three-dimensional model of innovation diffusion and suggested the three key drivers of innovation as the goodwill of the product, the selling price, and the marketing efforts. Many researchers also argued that the substitution rate of a technology product by an advanced generation product largely depends on the price and relative performance of both the products. Steeneck et al. (2016) presented a procedure for estimating demand for substitutable products when the inventory record is unreliable and only validated infrequently and irregularly. Hassandoust et al. (2016) laid down a framework giving the details of the information systems infusion factors as existing in the literature. Thakurta et al. (2018) identified the key factors that drive users of traditional computers to switch to tablet ones. Vejlgaard (2018) took the example of the television industry and advocated that culture plays an influential role in the diffusion of innovation and hence conclude that modeling of the same cannot be pure science. He also studied the influence of the culture upon the rate of adoption of an innovation. Kumar (2019) tried

that the social capital benefits with the innovations. Hambrick (2019) studied the innovation diffusion in the light of the new product launches at GoPro, an American technology firm engaged in the manufacturing of action cameras, development of mobile apps, and video editing software; and used the same framework and to forecast the short-term and long-term market potential of the company.

Innovation models can be broadly specified into two categories: based on the statistical behavior of potential adopters and the individual decision-making characteristics of the potential adopters (Li and Sui 2011). The Table2.4 shows the cross-tabulation of a few very popular works on diffusion modeling and classification of the same into broad categories.

Table2.4. History of research on modeling of innovation diffusion

Author(s) and Year	Multiple generations	Repeat purchase	Aggregate/ micro level	Leapfrogging
Bass (1969)	No	No	Aggregate	No
Fisher and Pry (1971)	Yes	No	Aggregate	No
Blackman (1974)	Yes	No	Aggregate	No
Bretschneider and Mahajan (1980)	Yes	No	Aggregate	No
Kamakura and Balasubramanian (1987)	Yes	No	Aggregate	No
Norton and Bass (1987)	Yes	No	Aggregate	No
Kalish (1985)	Yes	No	Aggregate	No
Wilson and Norton (1989)	Yes	No	Aggregate	No
Lilien and Yoon (1990)	Yes	No	Aggregate	No
Bayus (1992)	Yes	No	Aggregate	No
Mahajan and Muller (1996)	Yes	No	Aggregate	No
Lilien et al. (1981)	Yes	Yes	Aggregate	No
Rao and Yamada (1988)	Yes	Yes	Aggregate	No
Hahn et al. (1994)	Yes	Yes	Aggregate	No
Kim, Srivastava, and Han (2001)	Yes	Yes	Individual	Yes
Young (2009)	No	No	Individual	No
Bridges et al. (1995)	No	No	Individual	No
Winer (1985)	No	No	Individual	No
Wejnert (2002)	No	No	Individual	No
Jiang and Jain (2011)	Yes	Yes	Individual	Yes
Sachdeva et al. (2016)	No	No.	Individual	No
Benhabib, Perla, and Tonetti (2019)	No	No	Individual	No

The extant research on the diffusion of innovations has been very helpful to the academic researchers, practitioners as well as policymakers. The beauty of the existing research is that it can be applied to the physical good s' innovations as well as service innovations. The existing research has also been able to quantify the diffusion rate of innovations by quantifying the socio-cultural phenomenon that drives the spread of innovations in the market. The literature on diffusion modeling has been fairly exhaustive and comprehensive. There also exists plenty of work on advertising influence, optimal pricing, dynamic pricing, and optimal launch timing of new products. Many of the existing models have also been validated with the real-life data of the innovation launches, and have been proved to be a reliable predictor of the diffusion rates. They have been of great utility to the policymakers while coming up with the social welfare models that disrupt the behavior of the common public for social gains. Also, they have helped the businesses to accurately and precisely predict the sales patterns of the new launches and plan accordingly.

Thus, it can be inferred that the literature of forecasting the innovation diffusion is already fairly vast with a significant portion of it also covering the interface between the operations and marketing. However, the study on the impact of innovation diffusion on inventory policies for multi-generation products is still scarce as can be discovered in the upcoming sections.

2.4. Review of Inventory Modelling for Multiple Item Situations and Joint Replenishment

A subset of the inventory literature is the work on multi-item inventory models that deal in the management of more than one product in the supply chains. Since while dealing with technology generations, the supply chains of multiple products need to be planned and managed simultaneously, Table2.5 summarizes a few of the popular multi-item inventory models in the existing literature. Since inventory modeling is a very vast area, this review is mostly limited to that of the joint replenishment of multiple items. There has been significant research work on the multi-items inventory. A few of these studies are on substitutable products, a few of them on complimentary products, while a major part is on multiple products which may neither be complimentary nor substitute. There has been a decent amount of research work on multi-items inventory modeling and joint replenishment. There has also been significant work on joint replenishment policies for multiple items. Aksoy et al. (1988) worked upon the replenishment models with the shared setup costs to produce savings. Boctor et al. (2004) considered deterministic and time-varying demands with common ordering costs to formulate the joint replenishment models for multiple items. Bhattacharya (2005) worked upon the inventory model for two deteriorating items that follow a linear stock-dependent demand. Bayindir et al. (2006) built the replenishment models for variable production costs considering the economies of scale. Pasandideh et al. (2010) developed EPQ models for multiple products with warehouse capacity constraints under discrete delivery in the form of pallets and backlogging of demand. Sana (2010) developed the EOQ model for multiple items under deterioration and amelioration. Taleizadeh et al. (2011) developed the EPQ model for multiple items allowing the back-ordering and rework.

Qu et al. (2015) advocated that the Joint Replenishment policy can obtain better solutions than the Individual Replenishment policy. Wang, et al. (2015) proved that improved fruit fly optimization with random perturbation has better comprehensive performance than the original FOA, differential evolution algorithm, and particle swarm optimization algorithm. Chakraborty (2015) formulated the multi-item integrated supply chain model for deteriorating items with stock dependent demand under fuzzy random and fuzzy environments. Yadavalli et al. (2015) discovered that in the case of deteriorating products, as the mean perishing time for any product decreases, the mean stationary rate of replenishments increases. Feng et al. (2015) emphasized that the managers need to group and consolidate replenishment orders of different products to save on the ordering cost. This, in turn, requires the inventory levels to be set in a way to ensure simultaneous diminishing and triggering of replenishment orders.

Pareira and Gomes (2017) developed the EOQ Model for multiple products while allowing back-orders and incremental discounts on the pricing. Pasandideh et al. (2018) modeled the joint replenishment problem for several products under VMI policy and solved it with the use of meta-heuristics. Taleizadeh et al. (2019) worked upon the production modeling of multiple items taking due consideration of the policies related to quality appraisal and re-work. Chen et al. (2019) prepared a joint replenishment algorithm for partial demand substitution. Thus it can be argued that research on joint replenishment for multiple items has received creditable references in inventory research. The Table2.5 gives a summary of prominent studies on multi-item inventory modeling.

Table2.5. Summary of research studies on Inventory Optimization for multi-item products

Author	Method	Demand	A	B	C	D
Salameh et al. (2014)	Modeling and XL Solver	Deterministic and constant	✓	✓	⊗	⊗
Qu et al. (2015)	Genetic Algorithm, Hybrid Differential Evolutionary Algorithm, HSDEE (Hybrid self-adapting differential evolutionary algorithm)	stochastic	✓	⊗	⊗	⊗
Ongkunaruk et al. (2016)	Genetic Algorithm, Differential Evolutionary Algorithm	deterministic and constant	✓	⊗	⊗	⊗
Chen et al. (2016)	Genetic algorithms	deterministic and constant	✓	⊗	⊗	⊗
Chanda and Kumar (2011)	Nonlinear optimization	Innovation Diffusion influenced	⊗	⊗	✓	⊗
Chanda and Kumar (2012)	Nonlinear optimization	Innovation Diffusion influenced	⊗	⊗	✓	⊗
Chanda and Aggarwal (2014)	Nonlinear optimization	Innovation Diffusion influenced	✓	✓	✓	✓
Chanda and Kumar (2016)	Nonlinear optimization	Innovation Diffusion influenced	⊗	⊗	✓	⊗
Chanda and Kumar (2017)	Nonlinear optimization	Innovation Diffusion influenced	⊗	⊗	✓	⊗
Chanda and Kumar (2019)	Nonlinear optimization	Innovation Diffusion influenced	⊗	⊗	✓	⊗
Nagpal and Chanda (2019)	Nonlinear optimization and heuristics	Innovation Diffusion influenced	✓	✓	✓	✓
Kumar et al. (2013)	Nonlinear optimization	Innovation Diffusion influenced	⊗	⊗	✓	⊗
Kumar and Chanda (2016a)	Nonlinear optimization	Innovation Diffusion influenced	⊗	⊗	✓	⊗

Kumar and Chanda (2016b)	Nonlinear optimization	Innovation Diffusion influenced	⊗	⊗	✓	⊗
Kumar and Chanda (2018)	Nonlinear optimization	Innovation Diffusion influenced	⊗	⊗	✓	⊗
Wang et al. (2012)	Differential Evolutionary Algorithm	Deterministic	✓	⊗	⊗	⊗
Taleizadeh et al. (2011)	Fuzzy INLP, genetic algorithm, Particle Swarm Optimization	LR Fuzzy	✓	⊗	⊗	⊗
Deflem and Nieuwenhuyse (2013)	Linear programming	Poisson process	⊗	✓	⊗	⊗
Braglia et al. (2017)	Nonlinear minimization algorithm and metaheuristics	stochastic	✓	⊗	⊗	⊗
Flamand (2018)	Mixed Integer Programming	stochastic	⊗	✓	⊗	⊗
Holzapfel et al. (2018)	Generalized Assignment Problem; Mixed-integer programming	deterministic and constant	⊗	⊗	⊗	⊗
Hubner and Kuhn (2015)	Heuristic procedure	stochastic	⊗	✓	⊗	⊗
Hubner and Schnaal (2016)	Mixed-integer problem	stochastic	⊗	✓	⊗	⊗
Hubner and Schnaal (2017)	Specialized heuristic model	stochastic	⊗	✓	⊗	⊗
Paul et al. (2014)	Mixed-integer nonlinear programming	deterministic	✓	⊗	⊗	⊗
Kuo and Huang (2012)	Dynamic programming	price-dependent demand	⊗	✓	⊗	✓
Zhang et al. (2012)	Heuristic approach	correlated demand	✓	✓	⊗	⊗
Saracoglu et al. (2014)	integer linear programming, genetic algorithm	deterministic, seasonal, or variable depending upon the nature of products	⊗	⊗	⊗	⊗
Talebian et al. (2013)	Stochastic dynamic programming, Bayesian updating	Stationary demand	⊗	✓	⊗	⊗
Vulcano et al. (2011)	Demand estimation using a combination of multinomial logit (MNL) choice model with a non-homogeneous Poisson model of arrivals over multiple periods	Posson distribution	⊗	✓	⊗	⊗
Vaagen et al. (2011)	Stochastic programming	Stochastic	⊗	✓	⊗	⊗
Chakraborty et al. (2015)	Genetic algorithm	stock dependent	⊗	⊗	⊗	⊗
Chakraborty et al. (2013)	Genetic algorithm	variable	⊗	⊗	⊗	⊗
Jiangtao et al. (2014)	Lagrange approach, and line Search algorithms	stock dependent	⊗	⊗	⊗	⊗
Yadavalli et al. (2015)	Linear Programming	constant	⊗	✓	⊗	⊗
Gutiérrez et al. (2013)	a heuristic procedure based on the smoothing technique	Exponential smoothing	⊗	⊗	⊗	⊗
Ho et al. (2014)	Replenishment cycle division method; multi-item integration model	constant and known	⊗	⊗	⊗	⊗

Tsao and Sheen (2012)	profit optimization models, with credit periods and weight freight cost discounts	price dependent	⊗	⊗	⊗	⊗
Sana et al. (2014)	Profit maximization through genetic algorithm	stochastic	⊗	⊗	⊗	⊗
Buchbinder et al. (2013)	Primal-dual competitive algorithms	deterministic and constant	✓	⊗	⊗	⊗
Büyükkaramikli et al. (2013)	Cost minimization	stochastic Poisson demand	✓	⊗	⊗	⊗
Coelho and Laporte (2014)	branch-and-cut algorithm	stochastic demand	✓	⊗	⊗	⊗
Ligang et al. (2014)	Differential evolutionary algorithm	stochastic	✓	⊗	⊗	⊗
Dror et al. (2012)	Sensitivity analysis of costs	deterministic	✓	⊗	⊗	⊗
Elomri et al. (2012)	Cooperative game theory, Fractional programming	Deterministic	✓	⊗	⊗	⊗
Moon et al. (2011)	Heuristics and RAND Algorithm	deterministic	✓	⊗	⊗	⊗
Verma et al. (2014)	Cost minimization through non-linear programming	deterministic	✓	⊗	⊗	⊗
Wang et al. (2012)	differential evolution algorithm	stochastic	✓	⊗	⊗	⊗
Wang et al. (2013)	Fuzzy simulation differential algorithm	deterministic and uniform	✓	⊗	⊗	⊗
Wang et al. (2015)	Fruit fly optimization, Swarm collaboration, Random perturbation	deterministic and constant	✓	⊗	⊗	⊗
Zhang et al. (2011)	Mixed-integer non-linear programming	deterministic	⊗	✓	⊗	⊗
Zhang (2012)	Mixed-integer non-linear programming	deterministic	⊗	✓	⊗	⊗
Feng et al. (2015)	Cost optimization with heuristic algorithms	stochastic	✓	✓	⊗	⊗

A: Joint replenishment, B: Substitution, C: Technology products, D: Multi-generational products

2.5. Review of Inventory Modelling for Substitutable Products

A further subset of multi-item models is the models on substitutable products. This section throws light on the demand substitution work done till now. The research on substitution demand modeling dates back to the early 1970s. Mosenson, a Ph.D. student at MIT, in the Ph.D. thesis submitted by him in 1970, proposed the solution to the product substitution problem. Mosenson and Dror (1972) came up with the possible patterns of qualitative substitution and complementarity among different goods. They defined substitution patterns as the system of substitution relationships among nC2 in the context of consumer demand.

Beginning with the assortment optimization, the early studies in the 1970s (Pentico, 1974 and Pentico, 1976) focussed on assortment optimization where the seller deals in limited product variety owing to the resource constraints. Pentico (1988) extended the assortment based substitution to two factors by taking into consideration the length as well as the strength of the steel beams while studying their substitutability. The strategy of assortment optimization is used by many retailers (Quelch & Kenny, 1994). Rationalizing the range of assortment helps retailers optimize the costs and profits (Smith & Agrawal, 2000). The cost reductions with the rationalization results from the fact that demand volumes for each of the variants increase with a smaller range. While the studies written in the twentieth century considered the identicalness of prices and cost structures among the substitutable products for the sake of modeling simplicity, the latter set of studies in the current century have considered the case of un-identical costs and prices also (Li et al. 2007).

Coming to inventory optimization for substitutable products, McGullivary and Silver (1978) was the first one to consider the demand substitution arising due to the stock-out of the referred product. Drezner et al. (1995) extended the EOQ Model of Harris to incorporate the effect of product substitution caused by the stock-out of the preferred product. Khouja et al. (1996) came up with the first version of the newsboy model for two items with substitutable demand. Bassok et al. (1999) said that the product substitution offers the vendors a chance to pool their inventories and achieve lower inventory costs, which was later reinforced by Hsu et al. (2005). While the studies in the 1990s (Pasternack & Drezner, 1991; Hsu & Bassok, 1999) started with two substitutable products, the later studies (Rao et al. 2004; Shah & Avittathur, 2007; Huang et al. (2011) have been extended to a set of n substitutable products, where n is any positive integer. Also, there have been many joint models on pricing and inventory in the twenty-first-century research such as Hopp et al. (2005); Maddah & Bish (2007); Karakul and Chan; 2008); Akan et al. (2013); Yu et al. (2017) and many others. Within inventory optimization on substitutable products has also covered multiple perspectives such as joint replenishment (Yadavalli et al. 2006), information diffusion (Ganesh et al. 2008), supply chain coordination (Kraiselburd et al. 2004), re-manufacturing (Li et al. 2006; Bayinder et al. 2007).

When the choice models have been talked about, the studies also differ in the variety. While some of the studies have considered static choice models (Smith & Agrawal, 2000; Gaur & Honhon, 2006), some have considered dynamic choice models (Yucel et al. 2009). While some studies have assumed the location choice models in which the customers substitute the demand between the neighboring variants (Li, 2007), many of the studies have assumed multinomial choice logit models (Suh & Aydin, 2011; Aouad et al. 2018), with Hopp & Xu (2005) considering the Bayesian Logit Model. Many of the research articles have taken the decision choice to be a Markov chain phenomenon (Bayinder et al. 2005; Yu et al. 2017; Desir et al. 2020). While Lin & Sibdari (2009) deployed a discrete choice model, Etebari (2020) used the nested logit model to capture the customer's choice process rather than the multinomial logit model considering that the latter one suffers from the independence of irrelevant alternatives limitation.

The nature of demand pattern considered in the literature also spans from deterministic (Gurnani & Drezner, 2000; Lang & Domschke, 2010) to probabilistic (Pentico, 1974; Pasternack & Drezner, 1991; Kraeselburd et al. 2004; Rao & Swaminathan, 2004) and from Poisson distribution (Yadavalli et al. 2006; Xu et al. 2010; Burnetas & Kanavetas, 2018) governed to innovation diffusion governed (Chanda, 2011; Chanda & Agrawal, 2014; Chanda & Das, 2015).Looking at the literature that talks of technological substitution, Chanda (2011) proposed a model to determine the optimal price and quality for two substitutable generations of technology products. Chanda and Agarwal (2014) came up with the inventory optimization model for the two substitutable technology product generations. Chanda and Das (2015) discussed the dynamics of how technology generations get diffused in the market. Some of the prominent earlier works in the area of multi-generation substitution are Bass (1969), Norton & Bass (1987), Mahajan & Muller (1996), Islam & Meade (1997), Jun & Park (1999), Kim et al. (2000), Danaher et al. (2001), Chanda & Bardhan (2008), and Jiang & Jain (2012).

After having been introduced to the variety of work in terms of assortment optimization, inventory optimization, pricing optimization, choice models, and technological substitution, the upcoming paragraphs discuss some of the studies in chronological sequence published in past twenty years. To begin with, Pasternack and Drezner (1991) discussed a single-period inventory model for two products with stochastic demand where items will substitute with each other. The problem related to the approximation of the true demand rates and substitution rates in case of stock-out based substitution between multiple products was solved through the methods proposed by Anupindi et al. (1998). Bassok et al. (1999) showed the benefits of considering the substitution possibilities at the stage of ordering as compared to without considering the same while ordering.

Extending the concept of product substitution in the manufacturing context, Balakrishnan and Geunes (2000) examined how flexible the bill of materials with substitutable components and sub-assemblies can help reduce the inventories. Smith and Agrawal (2000) formulated a stochastic demand model for substitutable items and an inventory optimization approach for profit maximization under resource constraints. In 2001, the basic version of the newsvendor model was extended to a scenario where an item with extra inventory can substitute the demand for an understocked item (Rajaram and Tang, 2001). Mahajan and Van Ryzin (2001) discussed a single-period, stochastic inventory model for substitutable product variants within a retail assortment when there are shortages. Inderfurth (2004) and Xu et al. (2011) developed the optimal production model for the firms that are into the manufacturing of new products as well as refurbishing of used products, both being substitutable. Netessine and Rudi (2003) considered a consumer-driven substitution problem with an arbitrary number of products under both centralized inventory management and competition. Rao et al. (2004) considered one way downward substitution for stochastic demand in a multi-item inventory problem. Shin et al. (2005) suggested that the existing models on inventory planning of substitutable items can be classified based on modeling objectives and the nature of the substitution. Li et al. (2006) developed an optimal production planning problem for multiple products with demand substitution and remanufacturing of returned products. Wei and Fengheng (2007) worked on the inventory optimization of two substitutable products as a two-stage stochastic non-linear program. Wei and Fengsheng (2007) formulated the inventory management problem for two end-products with substitution as a two-stage stochastic nonlinear program. Shah and Avittathur (2007) developed the heuristics for solving the twin problem of the optimal assortment and optimal inventory in the retailing context under demand substitution and cannibalization. Kok and Fisher (2007) developed an assortment optimization model in which the customer may buy a substitute in the event of unavailability of his/her favorite product.

Nagarajan and Rajagopalan, (2008) examined inventory policies for substitutable products with stochastic demand. Chen and Plambeck (2008) proved that inventory levels can be reduced by incorporating the learnings of substitution probabilities in the demand model. Li and Ha (2008) studied how the reactive capacity can help reduce the gap between the supply and uncertain demand in case of substitutable products. Hopp and Xu (2008) studied how the interdependent decisions of assortment, inventory, and price under demand substitution can be optimized by approximating the demand substitution behavior. Nagarajan and Rajagopalan, (2008) examined inventory policies for substitutable products with stochastic demand.

Shumsky and Zhang (2009) worked upon the optimal capacity allocation policy when multiple products correspond to multiple demand classes and customers can upgrade to higher demand class in the event of capacity depletion of their original demand class. Yucel et al. (2009) did the research work on optimal assortments in customer-driven demand substitution considering the practical issues related to supplier selection, product quality, and shelf space limitations. Bish et al. (2009) while exploring the case of a monopolist firm producing two items with substitutable demand under flexible capacity showed how the optimal capacity decision gets influenced by key demand parameters such as market size, market risk, and nature of uncertainty. Tang and Yin (2009) developed a model for the joint determination of lot size and retail price of two substitutable products under fixed and variable price strategy. Pineyro and Viera (2010) while studying the problem of substitution between a new product and remanufactured product, found it to be NP-hard, and proposed a near-optimal solution of the problem with a tabu search based procedure. Dawande et al. (2010) said that the production decisions in the case of substitutable products are dependent upon the trade-off between the changeover costs and substitution costs. Gurler and Yilmaz (2010) considered a supply chain relationship between a retailer and manufacturer for two substitutable products where the retailer can return the unsold inventory to the manufacturer. Xu et al. (2010) worked upon optimal replenishment norms of substitutable products when the demand follows the Poisson distribution which is non-stationary by nature. Rusmevichientong et al. (2010) and; Agrawal et al. (2016) worked on an online assortment optimization problem with a multinomial logit model based consumer choice model and dynamic demand learning by the retailers. Asad and Demirli (2010) developed MILP for optimal production scheduling under demand substitution in the steel rolling mills. Dutta and Chakraborty (2010) studied the single-period inventory model for two items with one-way substitution in the fuzzy environment.

Vaagen et al. (2011) discussed the challenges and complexities that arise in a supply chain due to the demand uncertainty for consumer-driven substitutable products. Deflam and Nieuwenhuyse (2011) developed periodic inventory systems for two items under one-way substitution that optimize the total costs on a per-unit-time basis. Zhang et al. (2011) and Zhang et al. (2012) discussed the deterministic EOQ Model and heuristic algorithm for joint replenishment problem for multiple substitutable items under partial and complete back-ordering respectively. Zhang (2012) extended the partial backlogging model to the minor components accompanying the major items. Goyal and Netessine (2011) said that demand uncertainty in the case of substitutable products can be better mitigated by product flexibility rather than volume flexibility in the supply chain processes. Huang et al. (2011) studied the extension of the newsvendor problem with multiple products and partial product substitution. Amini and Li (2011) developed the integrated production planning and sales planning model when the new products are getting diffused in the market and substituting the earlier products. Honhon et al. (2011) developed the dynamic programming algorithm to find out the optimal assortment planning and inventory decisions in a single-period problem with stock-out based substitution. Suh and Aydin (2011) developed the pricing problem for substitutable products whose demand is governed by a multinomial logit choice model influenced by the product price. Kim and Bell (2011) studied the impact of price-influenced substitution on a firm's pricing decisions when it sells to multiple customer segments. Zhao et al. (2012) analyzed the pricing problem of two substitutable products under imprecise manufacturing cost and customer demand using the game theory. Zhang (2012) developed MINLP EOQ models with partial back-ordering and correlated demand of multiple minor items.

Tan and Karabati (2013) developed inventory policies with a random substitution rate for substitutable items with lost sales if the second-choice item is also not available. Akan et al. (2013) discussed how the manufacturer's ability to synchronize the product returns with the sales of a remanufactured product can help optimize the profit in case of substitution between a new product and a remanufactured product. Sainathan (2013) considered the demand substitution between competing perishable product variants where the product in the initial period of its shelf life has a higher perceived quality than the one in the later period of its shelf life. Saure and Zeevi (2013) showed how a retailer can learn about consumer preferences by offering different assortments and observing the consumer's reactions, and incorporate that learning into his assortment planning exercise. Although Ganesh et al. (2014) said that the substitution reduces the need for information sharing by pooling the inventories. However, that is valid only for functional products and not for technology gadgets. Fisher and Vaidyanatham (2014) also developed a demand estimation method for substitutable products in retail assortments. Newman et al. (2014) examined how choice-based models can be estimated using the sales data in case of multiple substitutable products being sold by a single firm. Salameh et al. (2014) proposed a joint replenishment model for substitutable demand. Vaagen et al. (2014) discussed the challenges and difficulties arising when approaching and modeling the consumer-directed substitution problem in quick response supply chains.

Krommyda et al. (2015) optimized the order quantities for two substitutable products with stock dependent demand. Ma et al. (2015) extended the basic single product newsvendor model to a multi-product newsvendor model with demand substitution and developed computational algorithms for optimal assortment and optimal order quantities. Chen et al. (2015) linked the inventory models for substitutable items with customer service objectives. Tan and Karabati (2013), Hubner et al. (2015), and Hubner and Schnaal (2017) study inventory planning under demand substitution in the context of retail assortments. Yadavalli et al. (2015) developed the inventory systems for two substitutable and perishable products under adversities. Avsar and Gursoy (2015) analyzed the substitutable product inventory problem using the concepts of stochastic game theory. He emphasized that since retailers compete for the substitutable demand, ordering decisions of each retailer depends on the ordering decision of the other retailer. Chen et al. (2015) suggested a single period stochastic inventory model for two substitutable items. Shin et al (2015) reviewed the literature on the inventory policies of substitutable items published during the four decades and classified the models based on the nature of the substitution.

Giri et al. (2016) explored a competition of selling two substitutable products and one complimentary product in two-echelon supply chain systems. Goyal et al. (2016) showed that the assortment planning problem with dynamic substitutions under stochastic demand is NP-hard even for a simple consumer choice model. Xu et al. (2016) developed an inventory model for a flexible substitution scheme in which the supplier has the flexibility to offer or not to offer the substitution and the customer has the flexibility to accept or reject it, and solved it using stochastic dynamic programming approach. Wei and Zhao (2016) studied pricing for substitutable products in a fuzzy environment. Hubner and Kuhn (2016) The heuristic procedure produces close-to-optimal solutions and outperforms the Kok and Fisher heuristic concerning both computational time and solution quality. Hubner and Schnaal (2016), and Hubner and Schnaal (2017) concluded that the appropriate consideration of space elasticity and substitution effects is essential. Ongkunaruk et al (2016) provided the evidence that a higher percentage of defective items leads to a lower optimal family cycle length, a higher-order quantity for each item, and a higher total expected cost per unit time. Chen et al. (2016) illustrated that a genetic algorithm with tournament selection performs better than an evolutionary algorithm in terms of the total expected cost and computation lead time. Braglia et al (2017) proposed alternative heuristics for stochastic joint replenishment that are efficient and seem therefore better than optimization algorithms. Zeppetella et al. (2017) considered the demand substitution under a make-to-stock environment under capacity and production constraints and optimized the production schedule. Vasanthi and Kamaraj (2017) defined various performance measures for the inventory system of substitutable items and provided a framework for computing the long-run inventory costs in such situations. Mishra and Shanker (2017) proposed that there is a cost of substitution also. Shanker (2017) considered an additional cost of substitution involved for each unit of the substituted item and considered the demand to be deterministic and constant. Vasanthi and Kamaraj (2017) presented continuous review inventory systems in a supply chain with two different substitutable items in stock. They assumed the demand for the products to follow an independent Poisson process.

Pan et al. (2018) developed a stock-based substitution model for two products. Shlapp and Fleishmann (2018) derived the optimal inventory policy for a firm selling multiple products that are partially substitutable under capacity constraints. Duong et al. (2018) studied the effects of the three factors (i.e. uncertain consumer demand, product lifetimes, and consumer substitution among the product range) on inventory performance. Flamand (2018) selected a composite assortment of fast-movers and high-impulse product categories and constructed an effective retail shelf space allocation that promotes shopping convenience and unplanned purchases. Holzapfel (2018) argued that there are other interdependencies also for multi-item inventories. These can be between inbound transportation, outbound transportation, and in-store logistics as well as capital tied up in inventories and differences in picking costs between the warehouses. Chen et al. (2019) worked on partial substitution for defective items, allowing the shortages. This study discovered that the differential evolution performs best in terms of the minimum total cost among the three heuristic solution methods used. Substantial number researches on varied dimensions for multi-items inventory management from the perspective of retailers is already been published as reviewed by Kok et al. (2006), Hubner and Kuhn (2012), and Mou et al. (2017).

Chen at al. (2015) and; Chen and Cao (2020) showed how the information on substitution rates and primary demand rates can be learned from the sales data on the fly. Dong et al. (2020) developed optimal pricing strategies for maximizing the expected profit.The Figure2.5 shows the word cloud drawn based on the keywords in the research articles. Since the models on demand substitution were the key agenda of our review, the word cloud captured these words as the prominent key terms in these studies.

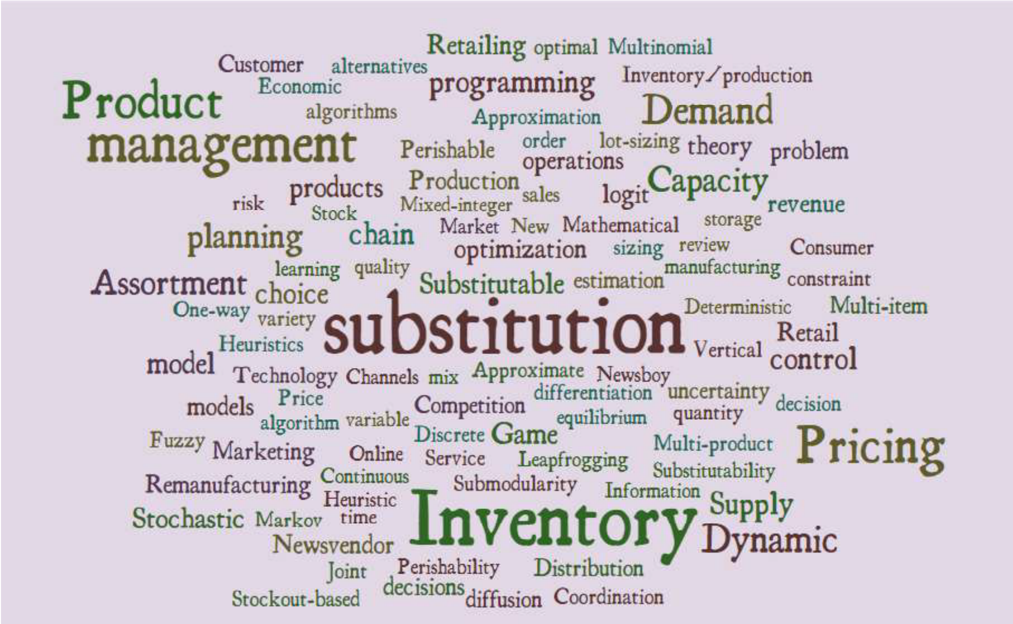

Figure2.5. Word Cloud formed from the keywords and abstracts of the research articles

In the following few pages, the two tables have been drawn. The Table2.6 captures the objective (viz. assortment optimization, inventory optimization, and price optimization), the nature of demand substitution (viz. assortment based, inventory-based, price-based, or technology-based), the propelling factor behind the substitution (viz. customer or vendor) and the direction of demand substitution (unidirectional or bi-directional), and the type of model used (viz. profit maximization or revenue maximization or utility maximization or cost minimization). The Table2.7 captures the solution approach used in the studies (viz. genetic algorithm, linear programming, game theory, newsboy model, nonlinear programming, mixed integer programming, stochastic programming, dynamic programming, etc.).

Table2.6. Analysis of existing literature on modeling for substitutable products in terms of objective, nature of substitution, and Model used

Legends AO: Assortment Optimization, IO: Inventory Optimization, PO: Price Optimization, CO: Capacity Optimization, AB: Assortment Based, SB: Stock-Based, PB: Pricing-Based, TB: Technology-based, C: Customer Influenced, VI: Vendor Influenced, Uni: Uni-directional, Bi: Bi-directional, PM: Profit Maximization, RM: Revenue Maximization, UM: Utility Maximization, CM: Cost Minimization

Work	Study Objective				Nature of substitution				Propelling Force		Direction		Optimization Model			
	AO	IO	PO	CO	AB	SB	PB	TB	C	V	Uni	Bi	PM	RM	UM	CM
Pentico (1974)	✓	×	×	×	✓	×	×	×	×	✓	✓	×	×	×	×	✓
Pentico (1976)	✓	×	×	×	✓	×	×	×	×	✓	✓	×	×	×	×	✓
McGillivray and Silver (1978)	×	✓	×	×	×	✓	×	×	×	✓	×	✓	×	×	×	✓
McGuire and Staelin (1983)	×	×	✓	×	×	×	✓	×	×	✓	✓	×	✓	×	×	×
Norton and Bass (1987)	×	✓	×	×	×	×	×	✓	✓	×	✓	×	×	✓	×	×
Parlar (1988)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Pentico (1988)	✓	×	×	×	✓	×	×	×	×	✓	✓	×	×	×	×	✓
Pasternack and Drezner (1991)	×	✓	×	×	×	✓	×	×	×	✓	×	✓	✓	×	×	×
Bitran & Dasu (1992)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	✓	×	×	×
Bitran and Gilbert (1994)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	×	×	×	✓
Chand et al. (1994)	✓	✓	×	×	✓	×	×	×	✓	×	✓	×	×	×	×	✓
Drezner et al. (1995)	×	✓	×	×	×	✓	×	×	×	✓	×	✓	×	×	×	✓
Khouja et al. (1996)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Lippman and McCardle (1997)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Birge et al. (1998)	×	×	✓	✓	×	×	✓	×	✓	×	×	✓	✓	×	×	×
Bassok et al. (1999)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	✓	×	×	×
Ernst and Kouvelis (1999)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Hsu and Bassok (1999)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	✓	×	×	×
Van Ryzin & Mahajan (1999)	✓	✓	×	×	✓	×	×	×	✓	×	×	✓	✓	×	×	×
Balakrishnan and Geunes (2000)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	×	×	×	✓
Duenyas and Tsai (2000)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	✓	×	×	×

Work	Study Objective				Nature of substitution				Propelling Force		Direction		Optimization Model			
	AO	IO	PO	CO	AB	SB	PB	TB	C	V	Uni	Bi	PM	RM	UM	CM
Gurnani and Drezner (2000)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	✓	×	×	×
Smith & Agrawal (2000)	✓	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Rajaram & Teng (2001)	✓	✓	×	×	×	✓	×	×	×	✓	×	✓	✓	×	×	×
Mahajan and van Ryzin (2001a)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Mahajan and van Ryzin (2001b)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Avsar and Gursoy (2002)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Agarwal & Smith (2003)	✓	×	×	×	✓	×	×	×	✓	×	×	✓	✓	×	×	×
Netessine and Rudi (2003)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Kraiselburd et al. (2004)	×	✓	×	×	×	✓	×	×	×	✓	×	✓	✓	×	×	×
Rao et al. (2004)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	×	×	×	✓
Bayindir et al. (2005)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	✓	×	×	×
Boyaci (2005)	×	✓	×	×	×	✓	×	×	×	✓	×	✓	✓	×	×	×
Cachon et al. (2005)	✓	×	×	×	✓	×	×	×	✓	×	×	✓	✓	×	×	×
Hopp & Xu (2005)	✓	×	✓	×	✓	×	×	×	✓	×	×	✓	✓	×	✓	×
Hsu et al. (2005)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	×	×	×	✓
Gaur & Honhon (2006)	✓	✓	×	×	✓	✓	×	×	✓	×	×	✓	✓	×	×	×
Li et al. (2006)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	×	×	×	✓
Bayindir et al. (2007)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	✓	×	×	×
Cachon & Kok (2007)	✓	×	✓	×	✓	×	×	×	✓	×	×	✓	✓	×	×	×
Kok & Fisher (2007)	✓	✓	×	×	✓	✓	×	×	✓	×	×	✓	✓	×	×	×
Li (2007)	✓	✓	×	×	✓	×	×	×	✓	×	×	✓	✓	×	×	×
Liu and Lee, (2007)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	×	×	✓	×
Maddah & Bish (2007)	✓	✓	✓	×	✓	×	×	×	✓	×	×	✓	✓	×	×	×
Serin (2007)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Shah and Avittathur (2007)	×	✓	×	×	×	✓	×	×	✓	×	✓	×	✓	×	×	×
Tang and Yin (2007)	×	✓	✓	×	×	×	✓	×	✓	×	✓	×	✓	×	×	×

Work	Study Objective				Nature of substitution				Propelling Force		Direction		Optimization Model			
	AO	IO	PO	CO	AB	SB	PB	TB	C	V	Uni	Bi	PM	RM	UM	CM
Wu et al. (2007)	×	✓	✓	×	×	×	✓	×	×	✓	✓	×	✓	×	×	×
Aydin and Porteus (2008)	×	✓	✓	×	×	×	✓	×	×	✓	✓	×	✓	×	×	×
Ganesh et al. (2008)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Hopp and Xu (2008)	×	✓	✓	×	×	✓	×	×	×	✓	×	✓	✓	×	×	×
Karakul (2008)	×	✓	✓	×	×	×	✓	×	×	✓	✓	×	✓	×	×	×
Karakul and Chan (2008)	×	✓	✓	×	×	×	✓	×	×	✓	✓	×	✓	×	×	×
Nagarajan and Rajagopalan (2008)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Sivakumar (2008)	×	✓	×	×	×	✓	×	×	×	✓	×	✓	×	×	×	✓
Bish et al. (2009)	×	×	×	✓	×	×	✓	×	×	✓	×	✓	✓	×	×	×
Dong et al. (2009)	×	×	✓	×	×	×	✓	×	✓	×	✓	×	×	✓	×	×
Gurler, Oztop, and Sen (2009)	×	✓	✓	×	×	✓	×	×	×	✓	✓	×	✓	×	×	×
Hsieh and Wu (2009)	×	✓	✓	×	×	×	✓	×	✓	×	✓	×	✓	×	×	×
Vaagen et al. (2009)	✓	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Yang and Schrage (2009)	×	✓	×	×	×	✓	×	×	✓	×	✓	×	×	×	×	✓
Yucel et al. (2009)	✓	✓	×	×	✓	✓	×	×	✓	×	×	✓	✓	×	×	×
Akcay et al. (2010)	×	×	✓	×	×	×	✓	×	✓	×	✓	×	×	✓	×	×
Bish and Suwandechochai (2010)	×	×	×	✓	×	×	✓	×	×	✓	×	✓	✓	×	×	×
Chiang (2010)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Dawande et al. (2010)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	×	×	×	✓
Deniz et al. (2010)	×	✓	×	×	×	✓	×	×	✓	×	✓	✓	✓	×	×	×
Dutta and Chakraborty (2010)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	✓	×	×	×
Fadiloglu et al. (2010)	✓	×	×	×	✓	×	×	×	✓	×	×	✓	✓	×	×	×
Gurler & Yilmaz (2010)	×	✓	×	×	×	✓	×	×	×	✓	×	✓	✓	×	×	×
Honhon et al. (2010)	✓	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Karakul and Chan (2010)	×	✓	✓	×	×	×	✓	×	×	✓	✓	×	✓	×	×	×

Work	Study Objective				Nature of substitution				Propelling Force		Direction		Optimization Model			
	AO	IO	PO	CO	AB	SB	PB	TB	C	V	Uni	Bi	PM	RM	UM	CM
Lang and Domschke (2010)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	×	×	×	✓
Pineyro & Viera (2010)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	×	×	×	✓
Tang & Yin (2010)	✓	✓	✓	×	×	×	✓	×	×	✓	×	✓	✓	×	×	×
Xu, Yao, and Zheng (2010)	×	✓	×	×	×	✓	×	×	✓	✓	✓	×	×	✓	×	×
Chanda (2011)	×	×	✓	×	×	×	✓	✓	✓	✓	✓	×	✓	×	×	×
Huang et al. (2011)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Stavrulaki (2011)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Xia (2011)	×	×	✓	×	×	×	✓	×	×	✓	✓	×	✓	×	×	×
Burkart et al. (2012)	×	×	✓	×	×	×	✓	×	✓	×	×	✓	×	✓	×	×
Pan & Honhon (2012)	✓	×	✓	×	✓	×	×	×	✓	×	×	✓	✓	×	×	×
Akan et al. (2013)	×	✓	✓	×	×	×	✓	×	×	✓	✓	×	✓	×	×	×
Deflem and Nieuwenhuyse (2013)	×	✓	×	×	×	✓	×	×	×	✓	✓	×	×	×	×	✓
Gilland and Heese (2013)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Honhon & Seshadri (2013)	✓	×	×	×	✓	×	×	×	✓	×	×	✓	✓	×	×	×
Tan and Karabati (2013)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Chanda & Aggarwal (2014)	×	✓	×	×	×	×	×	✓	✓	✓	✓	×	×	×	×	✓
Bernstein et al. (2015)	×	✓	×	×	✓	✓	×	×	✓	×	×	✓	×	✓	×	×
Chanda & Das (2015)	✓	×	×	×	×	×	×	✓	✓	✓	✓	×	✓	×	×	×
Chen et al. (2015)	×	✓	×	×	✓	×	×	×	×	✓	×	✓	×	×	✓	×
Cosgun et al. (2017)	×	×	✓	×	×	×	✓	×	×	✓	×	✓	✓	×	×	×
Li & Fu (2017)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Mukhopadhyay & Goswami (2017)	×	✓	×	×	×	✓	×	×	✓	×	✓	×	×	×	×	✓
Transchel (2017)	×	✓	×	×	×	✓	✓	×	✓	×	×	✓	✓	×	×	×
Yu et al. (2017)	×	✓	✓	×	✓	×	✓	×	×	✓	✓	×	✓	×	×	×

Work	Study Objective				Nature of substitution				Propelling Force		Direction		Optimization Model			
	AO	IO	PO	CO	AB	SB	PB	TB	C	V	Uni	Bi	PM	RM	UM	CM
Aouad et al. (2018)	✓	✓	×	×	✓	×	×	×	✓	×	×	✓	✓	×	×	×
Burnetas et al. (2018)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Ceryan et al. (2018)	×	×	✓	×	×	✓	✓	×	✓	×	×	✓	✓	×	×	×
Farahat & Lee (2018)	×	✓	×	×	✓	×	×	×	✓	×	×	✓	✓	×	×	×
Khademi & Eksioglu (2018)	×	✓	×	×	×	✓	×	×	×	✓	×	✓	×	×	×	✓
Schlapp & Fleischmann (2018)	×	✓	×	×	×	✓	×	×	✓	×	×	✓	✓	×	×	×
Surti et al. (2018)	×	✓	✓	×	×	✓	✓	×	✓	×	×	✓	✓	×	×	×
Wan et al. (2018)	✓	✓	×	×	✓	×	×	×	✓	×	×	✓	✓	×	×	×
Zhang et al. (2018)	×	✓	×	×	✓	×	×	×	✓	×	×	✓	✓	×	×	×
Aouad et al. (2019)	✓	✓	×	×	✓	×	×	×	×	✓	×	✓	✓	×	×	×
Feng et al. (2019)	×	✓	×	×	×	✓	×	×	✓	×	✓	×	×	×	×	✓
Fu et al. (2019)	×	✓	×	×	✓	✓	×	×	×	✓	✓	×	✓	×	×	×
Geunes & Su (2019)	✓	✓	×	×	✓	✓	×	×	✓	×	×	✓	✓	×	×	×
Jing & Mu (2019)	×	✓	×	×	✓	×	×	×	✓	×	✓	×	✓	×	×	×
Kim & Bell (2019)	×	✓	✓	×	×	✓	✓	×	✓	×	×	✓	✓	✓	×	×
Chan et al. (2020)	✓	✓	×	×	✓	✓	×	×	✓	✓	×	✓	✓	×	×	×
Jing & Mu (2020)	×	✓	×	×	✓	×	×	×	×	✓	✓	×	✓	×	×	×
Majumder et al. (2020)	×	✓	×	×	✓	✓	×	×	✓	×	×	✓	✓	×	×	×
Rasouli et al. (2020)	×	×	✓	×	✓	×	×	×	✓	×	×	✓	✓	×	×	×

Table2.7. The Solution Methodologies used in the research articles

Method Deployed	Author work
Markov	Duenyas and Tsai (2000); Bayindir et al. (2005); Liu and Lee, (2007); Sivakumar (2008); Yu et al. (2017); Desir et al. (2020)
Logit choice model	Rusmevichientong et al. (2010); Suh & Aydin (2011); Agrawal et al. (2016); Aouad et al. (2018)
Bayesian Logit Model	Hopp & Xu (2005)

Game Theory	McGuire and Staelin (1983); Parlar (1988); Birge et al. (1998); Avsar and Gursoy (2002); Netessine and Rudi (2003); Boyaci (2005); Serin (2007); Wu et al. (2007); Hopp and Xu (2008); Hsieh and Wu (2009); Chiang (2010); Tang & Yin (2010); Xia (2011)
Newsvendor Model	Pasternack and Drezner (1991); Khouja et al. (1996); Lippman and McCardle (1997); Ernst and Kouvelis (1999); van Ryzin & Mahajan (1999); Smith & Agrawal (2000); Mahajan and van Ryzin (2001a); Mahajan and van Ryzin (2001b); Netessine and Rudi (2003); Bayindir et al. (2007); Maddah & Bish (2007); Serin (2007); Shah and Avittathur (2007); Wu et al. (2007); Aydin and Porteus (2008); Karakul (2008); Karakul and Chan (2008); Vaagen et al. (2009); Yang and Schrage (2009); Dutta and Chakraborty (2010); Gurler & Yilmaz (2010); Karakul and Chan (2010); Huang et al. (2011); Stavrulaki (2011); Deflem and Van Nieuwenhuyse (2013); Maddah et al. (2014); Bernstein et al. (2015); Li & Fu (2017); Surti et al. (2018)
Dynamic Programming	Pentico (1974); Pentico (1976); Pentico (1988); Bitran and Gilbert (1994); Rao et al. (2004); Hsu et al. (2005); Li et al. (2006); Nagarajan and Rajagopalan (2008); Dong et al. (2009); Akcay et al. (2010); Honhon et al. (2010); Xu, Yao, and Zheng (2010); Wan et al. (2018); Fu et al. (2019)
Heuristics	Shah & Avittatathur (2007); Nagarajan & Rajagopalan (2008); Deniz et al. (2009)
Stochastic Programming	Bitran & Dasu (1992); Hsu and Bassok (1999); Netessine et al. (2002); Kraiselburd et al. (2004); Bish et al. (2009); Bish and Suwandechochai (2010)
Linear Programming	Agarwal & Smith (2003)
Greedy Search	Bassok et al. (1999)
MILP	Balakrishnan and Geunes (2000); Gaur & Honhon (2006); Lang and Domschke (2010); Pineyro & Viera (2010); Burkart et al. (2012)
Non-Linear Programming	Chand et al. (1994); Anupindi et al. (1998); Li (2007); Tang and Yin (2007); Honhon & Seshadri (2013); Chanda & Aggarwal (2014); Chen et al. (2015)

2.5.1. Review of EOQ models for technology products with technological demand substitution

From the above discussion, it can be argued that inventory literature on substitutable items is quite rich. Extensive research has been done to understand the impact of marketing-mix variables on EOQ policy using the product life cycle (Moon and Lee 2000, Teng et al 2003, Wu et al 2017). Unfortunately, little attention has been paid to explore the influence of life cycle dynamics to optimal replenishment policies of technology products using innovation-diffusion theory (Chanda and Kumar 2017). Niu (2006) suggested that the Bass model (1969) (one of the pioneer models in innovation-diffusion literature) should be used to model production, inventory, and capacity-planning process. Chern et al (2001), for the first time, used the Bass model (1969) to determine the optimal timing number of replenishments for technology products. Chanda and Kumar (2011) used Fourt and Woodlock (1960) framework to optimize the total cost of the inventory system per unit time. Kumar et al. (2013) studied the influence of the shape parameter of the demand function on the EOQ model. Chanda and Kumar (2017) used the fuzzy innovation diffusion demand model to explore EOQ policies with appropriate trade-credit policy for a technology product.

Most of the above models successfully considered lifecycle dynamics to minimize the total cost of replenishment of technology products. However, these models didn't consider one of the important aspects of technology adoption i.e. substitution-diffusion of generational products, a common phenomenon in the technology market. Ke et al (2013) suggested that often the inventory cost for generational products goes too high to influence the time-to-market of next-generation products. Still, research on the effect of the substitution phenomenon of generational items on inventory policies didn't get much attention. Ke et al (2013) proposed a framework to evaluate inventory cost by considering the adoption-substitution of successive generations' technology products. Chanda and Aggarwal (2014) argued that to develop inventory policies for successive generations' technology products, a technically superior demand model should be used to capture substitution effect across generations.

However apart from Nagarajan and Rajagopalan, and Chanda and Agarwal (2014), none of the models discussed substitution from the product generations' perspective, which is a general trend in the technology market. Chanda and Agarwal (2014) used the successive-generation innovation-diffusion demand framework to discuss inventory policies for two substitutable technology generations. One of the limitations of the Chanda and Agarwal (2014) model was its failure to capture the full life-cycle dynamics of technology products due to the exponential nature of demand function.

Although of late, few attempts were been made to incorporate the adoption-diffusion effect on inventory policies (Chanda and Kumar 2011; Kumar et al. 2013; Chanda and Kumar 2017; Kumar and Chanda 2018); but they are very restrictive. Chanda and Kumar (2011) formulated the EOQ model for dynamic innovation effect, which was later extended by incorporating the effect of inflation (Chanda and Kumar

2012). Kumar et al. (2013), Chanda and Kumar (2016), and Kumar and Chanda (2016a) tried to make the EOQ model more realistic by solving the model under the light of the fuzzy set theory. Kumar and Chanda (2016b) studied the EOQ model for the bimodal demand curve of the technology products. Chanda and Kumar (2016) studied the impact of pricing and advertising on the inventory of technology products under dynamic market potential. Chanda and Kumar (2017) extended this study further to incorporate the permissible delay in payments. Kumar and Chanda (2018) developed the inventory models for technology products under a two-warehouse scenario. Kumar, Aggarwal, and Chanda (2013), and Chanda and Kumar (2016) developed the EOQ model under the light of fuzzy set theory for technology items where demand follows innovation-diffusion theory. But that research used fuzzy logic only single-generation products and needs to be extended further to the scope of multi-generation products.

2.6. Review of inventory models for multi-product scenarios under trade credits

It is in the mutual interest of the retailer and the supplier to promote the product in the market (Miller & Orr, 1966; Schwartz, 1974; Schwartz & Whitcomb, 1979; Emery, 1984). With this objective of bringing higher volumes on the market shelf, the supplier provides some credit to the retailer to ease the working capital constraints of the retailer and to enable him to procure more volumes. The velocity of money also increases with trade credit (Zahen & Hosek, 1973). Trade credit is also viewed as a mechanism to separate the exchange of money from the uncertainty present in the exchange of goods (Ferris, 1981). The role of credit periods in modern trade cannot be ignored. Smith (1987) said that credit period information helps the sellers in identifying the prospective defaults more quickly than if the financial institutions were the sole providers of the credit. Suppliers may also act as debt collectors, and ensure the customers against the liquidity shocks (Cunat, 2007). Further, studies suggest that firms tend to use more of it during the crisis (Calomiris et al. 1995). Private firms located in particularly high social trust regions tend to use more of inter-firm credit (Wu et al. 2014). Inter-firm credit terms and credit policies vary widely among the different firms and across the industries (Smith et al., 1999). Trade credits also help in alleviating the problem of information asymmetry that lies between firms and banks (Biais and Gollier, 1997). The increased globalization has also triggered government initiatives on trade finance (Menichini, 2011). Thus, research on the importance of trade credit in the modern trade is in plenty.

Coming to the optimization for multiple items under trade credits, a substantial amount of studies have been done. Basu et al. (2006) developed the inventory models for multiple items with exponentially declining demand under three ranges of credit terms for the cycle time of the items. Tsao (2009) studied the impact of credit period and sales learning curve to determine the retailer's optimal promotional effort for multiple items under joint replenishment; and concluded that both the retailer and the supplier can earn a higher profit under a centralized decision model in the search algorithm to solve the EOQ model with advance payments done for multiple and high price raw contrast to that under the de-centralized decision model. Wang and Hu (2010) proposed a heuristic to solve the inventory model for the multiple substitutable components used in production in this era of modularization and customization. Min et al. (2010) developed an inventory optimization model to maximize the profits of a retailer facing the stock-dependent demand for multiple items under the trade credits mechanism. Dye and Ouyang (2011) showed that particle swarm optimization offers acceptable efficiency while solving the joint pricing and replenishment problem with fluctuating demand and trade credit financing. Tsao and Teng (2013) developed the two heuristic methods to solve the joint replenishment model for multiple items under trade credits. Das et al. (2014) allowed partial backlogging of demand and used a genetic algorithm to solve the model for multiple deteriorating items under inflation a credit period. Priyan and Uthayakumar (2014) developed a two-echelon inventory model with reverse logistics for multiple items under multiple constraints and trade credits mechanism. But the research that has linked inventory decisions with trade credits is rare in the case of technology products (the only two such works being Chanda and Kumar, 2017; and Chanda and Kumar, 2019), and missing in case of multiple technology generations.

2.7. Review of inventory models for multi-product scenarios under the price-dependent demand

It is an explicit fact that every product has a price elasticity of demand although the degree of elasticity may vary from one item to another (Eilon, 1975; Eilon & Cosmetatos, 1979; Eilon, 1983). As the price of the product falls, there is an increase in demand because more people find the product to be worth its price. Thus, diffusion of a product in the market is a function of its price. This effect of pricing on diffusion and inventory policies shall be studied in my research. It is also known that the nominal price of items generally increases with time in a growing economy due to inflation. While the real price of the technology products falls with time on account of technology maturation. This changes the purchase behavior of retailers.

Kar, et al. (2001) formulated the inventory model for multiple items with stochastic price-dependent demand where the objective function and constraints lack exactness. Feng (2010) proposed that dynamic pricing is more valuable when the procurement cost is high or when the demand is more elastic to price. Jain et al. (2012) explored the inventory optimization for the multiple items under price breaks and multiple set-ups for procurement and recovery. Tsao and Sheen (2012) studied the inventory model for multiple items under a discount on freight costs. Chakraborty et al. (2013) developed an inventory optimization framework for deteriorating multiple items with discounted pricing and fuzzy demand. Talebian et al. (2013) illustrated how pricing can be used as a tool for demand learning during the assortment planning of perishable products. Mousavi et al. (2014) formulated the multi-period inventory model for multiple items with price discounting. Lu et al. (2014) brought in the impact of volume-based price differentiation while studying the pricing and inventory decisions. Chew et al. (2014) studied the effect of price-dependent demand on the inventory management of perishable products. Feng et al. (2015) suggested that the joint dynamic pricing in the case of multiple substitutable products results in better pay-off as compared to static pricing.

Wei and Zhao (2016) considered manufacturing cost and customer demand as fuzzy variables to explore the effect of pricing strategies in the case of duopolistic manufacturers. Kaya and Polat (2017) examined the inventory decisions for price-dependent demand for perishable products. Chen & Dong (2018) examined the responsive pricing and procurement for a firm dealing in two correlated products with price dependent demand under uncertain supply capacities. Giri et al. (2020) showed that pure bundling in the case of complementary products offers higher benefits than when the products are sold at individual prices, but was silent on the pricing dynamics of substitutable products. The studies that have been done till date on considering the price influence on inventory, have been limited only to the functional products; except for Kuo and Huang (2012); and Chanda and Aggarwal (2014) that have examined the impact of pricing on inventory decisions for high technology products.

2.8. Review of inventory models for multi-product scenarios under storage space constraints

It is well known that the inventories need some storage space before they can be consumed. However, there exist often the storage space constraints that can be mitigated by renting additional space. But the per-unit cost of renting additional space is more than that of the captive storage space. A large number of models have been worked upon the two warehouse models, some of them by Liao et al. (2012) and Liao et al. (2013). Yao (2010) and Das et al. (2017) used genetic algorithms for inventory optimization under space constraints. Some studies (Hubner & Schnaal, 2016 and Hubner and Schnaal, 2017) have also used space elastic stochastic demand in which the larger size of the warehouse spurs the demand. Sana (2015), Minner and Silver (2005), Cheung & Simchi (2019) also used the stochastic demand patterns. A few studies have also considered the ramp type demand (Agarwal et al, 2013 and Chakraborty et al, 2018) and the Poisson distribution of demand (Minner & Silver, 2007).

One of the earliest works on the multi-item inventory models under storage space constraints was by Dixon and Poh (1990). Since deterioration of the products is a very natural phenomenon, around half of the studies have taken the effect of deterioration while formulating the inventory models under space constraints. There have been two reviews of the literature (Hubner & Kuhn, 2012 and Mou et al., 2017) done on inventory management under space constraints. But both of them have limited themselves to the context of retail management. Reddy et al. (2012) used Kuhn-Tucker conditions to solve inventory problems under multiple constraints. Jing and Mu (2020) developed a dynamic order quantity model for perishable and substitutable items under storage space limitations. Jackson and Munson (2019) studied the lot-sizing under joint replenishment for multiple products under capacity expansion provisions.

Thus, a significant amount of inventory research on multiple items under two warehouses has been carried out till now. However, the studies that have linked storage space constraints to the innovation diffusion dependent demand rate are not to be found in the inventory literature; except for one study by Kumar and Chanda (2018).

2.9. Review of inventory models for multi-product scenarios under imprecise environments

To date, the traditional optimization techniques have been used to solve the problems that have a well-defined structure, i.e. a specific objective function, specific constraints, and a precise mathematical solution. However, in the real world, the situations are not deterministic rather characterized by a lot of uncertainties and randomness (Bellman & Zedah, 1970; Casey, 2014; Bennett & Lemoine, 2014). The real-world environment in which to make decisions, the objectives, the constraints as well as the results expected from the possible actions are not known precisely. The fuzzy set theory and basic ideas of fuzziness have also been introduced to by Zimmermann (1976). Fuzzy set theory suggests methods of dealing with imprecision and uncertainty in a quantitative way.

Vujosevik et al. (1996) modeled the EOQ problem using fuzzy logic, assuming that the ordering cost and holding cost are not precisely known. Mondal and Maiti (2002) used a genetic algorithm to solve the multi-item EOQ model under fuzzy objective and imprecise constraints. Multiple substitutable items under uncertain demand using the newsvendor approach were considered for inventory modeling in the literature (Shao & Ji, 2006; and Dutta & Chakraborty, 2010). Taleizadeh et al (2011) developed meta-heuristic algorithms to solve single-period inventory problems under uncertain demand. Mahata and Mahata (2011) developed a fuzzy EOQ model for two levels of trade credit assuming that the retailer is in a powerful position to command full credit from the supplier while offering partial credit to the consumer. Maiti (2011) considered the planning horizon in the inventory model to be imprecise and used a genetic algorithm where the cross-over probability was derived using fuzzy logic. Pattnaik (2013) developed the fuzzy EOQ model for stock-dependent and price-sensitive demand. Soni (2013) developed a fuzzy framework for inventory modeling and coordinated pricing under partial trade credit financing by retailers. Taleizadeh et al (2009, 2010 and 2013) performed substantial research on constrained optimization of inventory using fuzzy set theory. Xu (2014) took the demand rate and the deterioration rate as fuzzy variables with known distributions while formulating the inventory optimization model under trade credit. Das et al. (2015) considered the credit period offered by the supplier to the manufacturer as a fuzzy variable and optimized the production run time. Majumder et al. (2015) developed the EPQ model under partial trade credit policy for deteriorating items with crisp and fuzzy demand. Mondal et al. (2015) developed the EOQ model under two-level partial trade credits while considering the demand to be dependent upon the credit period, amount of credit and inventory level, and inventory costs as fuzzy rough in nature. Roy (2015) considered the uncertain cycle time as a triangular fuzzy number and de-fuzzified the optimal results using the signed distance method.

Kumar and Goswami (2015) and Garai et al. (2016) employed the fuzzy expectation and the possibility/necessity measure to transform the fuzzy model into a deterministic NLP problem. Shekarian et al. (2016) investigated the different optimization techniques and algorithms that can be used for optimizing inventory under imprecise conditions. Garai et al (2017) derived the possibility, necessity, and credibility measures to determine the chances of occurrence of fuzzy events while modeling inventory for multiple items. Tripathy and Sukla (2018) considered the demand to be a ramp-type function while developing the EOQ model with fuzzy costs. Bera and Jana (2017) proposed an EPQ model for multiple products with stochastic demand. Manna et al. (2016) considered the planning horizon to be fuzzy while developing an EPQ model for multiple items with a learning effect on imperfect production. De and Mahata (2019) worked on multiple items with imperfect quality that can be sold as a single batch with a proportionate discount rate. Huang and Zhang (2019) studied the dynamics of diffusion between two competitive products in heterogenous consumer social networks with repeat purchase and said that there is an equilibrium at which both the products can co-exist. While there is a significant study that has been done on linking fizzy logic with inventory decisions, but it is scarce in the area of technology products and multigenerational products.

2.10. Research Gaps and Future Directions from Literature Review

This literature review suggests that researchers have made a noteworthy contribution to the vast area of inventory management of multi-item products which are substitutable in natures. But when it comes to the inventory optimization for successive generations of technology products with the short product life cycle, there is a lot more to be done to extend the existing research. Post the thorough review of the existing inventory modeling literature, the authors identified some areas of gaps in the existing literature which are elaborated in this section. There has been a lot of research to model the diffusion of such products; which has also been extensively handy to the practitioners in forecasting the demand and making sound operational as well as strategic decisions related to sales and operations. Also, there is plenty of research available on inventory modeling and optimization, but the research on the inventory modeling of innovative products is very scarce.

It is also apparent that the literature on replenishment policies for substitutable items is rich. But most of the above research was confined within the boundary of item-level substitution demand pattern. Kim et al. (2000) suggested that the demand for a technology product is not only linked with the dynamics of successive generations but also by the complementarities and competition with the other product categories. Kuo (2012) worked upon the linkage of inventories of multi-generation deteriorating products with dynamic pricing but kept the replenishment dynamics out of the purview. Chanda and

Aggarwal (2014) argued that for generational products, substitution rate strongly influences the optimal ordering policies of both generation products. Nagpal and Chanda (2019) discussed the effect of several trade-credit strategies on the inventory policies of substitutable product generations. Most of the existing literature barring the three works by Kuo and Hang (2012), Chanda and Aggarwal (2014), and Nagpal and Chanda (2019) considers the single generation products only. To the best of our knowledge, no EOQ model is developed in inventory literature that captures the substitution effect for technology generation products under a continuous review system. Thus, the work on inventory modeling of multi-generation products is still very rare.

First, though the above articles captured the substitution effect on inventory policies of technology generations, the models were developed for a single period replenishment cycle, the most of the work done on technology generations has mostly considered the innovation effect only while ignoring the imitation effect. It is well known that the word of mouth marketing also results in a significant proportion of total adoption. So, future studies should consider the imitation effect for the multi-generation products. Also, there is a need to develop robust multi-period inventory optimization models.

Second, the trade credits play an important role in the modern-day business, where both the buyer and the seller can have multiple incentives in using the credit terms. The credit terms sometimes influence the demand also along with innovation and imitation effect. At times, the sellers offer different credit terms for different generations of products to achieve the desired goals in the overall product portfolio. This needs to be discovered in future research.

Third, it is hard to find that technology products are price-inelastic to demand. Since the selling price influences the demand, the same needs to be factored in while formulating the demand function. The cross-elasticity of the price is also important since the sellers play with the prices of one SKU to influence the demand of the others. Many a times, inventory decisions have to be integrated with the product pricing decisions, which needs to be worked upon in the future research.

Fourth, generally, the businesses have limited storage space, and therefore the opportunity cost of storage space is significant. As the inventories increase, the cost of the storage per unit also rises because the firms have to rent an outside space at a higher cost than the domestic one. This tweaks the trade-off between the inventory ordering costs and inventory carrying costs. The increasing marginal cost of space per unit inventory makes it more desirable. Thus, it needs consideration in future research.

Fifth, the demand is not deterministic but stochastic, and sometimes even uncertain. Not only the demand, there can be uncertainty around the factors other than demand also, like the cost of space, selling price of the product, coefficients of innovation and imitation, etc. This uncertainty can be managed by using the fuzzy set theory for better optimization of inventories for technology generations.

2.11. Contributions of the Review

Particularly, the study adds value by bringing to the table the past work in this area and highlighting the gaps in existing research along with laying the future directions. From the perspective of theoretical contribution, this review discovers a lot of possible scenarios that can arise for multi-generation products. This understanding of the possible scenarios helps in categorizing the existing work, which is quite diffused in bits and pieces but also to generate insights on emerging business situations. This re-categorization of the models helps practitioners make out the limitations of the existing research.

This review also identifies areas for further research. If some research can be pursued in these suggested areas, that shall further consolidate the existing body of knowledge on inventory models for multi-generation products. The authors sincerely hope that this chapter will act as a foundation for existing research endeavors, catalyze future research on the advocated lines, and help practitioners to develop enhanced inventory models in a changing technological product landscape.

2.12. Research Methodology used in the thesis

This thesis shall be Quantitative research and shall come up with the new Operations Research models for inventory optimization of successive generation products. Before modeling the inventory, it shall propose a demand model for the technology generation products and validate the same on the existing datasets. Once the demand model has been validated, the same shall be used to develop a basic EOQ Model for the successive technology generations. After developing the basic EOQ Model for single-period inventory management, the basic multi-period EOQ model shall be formulated. And then, the thesis shall move on to extend these basic models to incorporate the effect of business realities such as credit terms, pricing dynamics, warehousing space dynamics, ambiguous business environment, etc.
The methodology for each of the EOQ models shall consist of the following steps:

a) Laying down the assumptions
b) Defining the objective function, constraints, decision variables, and input variables
c) Quantifying the differential equation that specifies the demand rate
d) Elaborating the Inventory equation
e) Quantifying the objective function
f) Solving the objective function with a numerical example
g) Performing sensitivity analysis
h) Deriving the managerial insights from the solution

Most of these models fall under the category of MINLP (Mixed Integer non-linear programming) since the objective function is non-linear, and there are integer constraints on the number of replenishments. Sometimes, there may be non-linear constraints also such as in case of limited storage space. The nature of objective functions and constraints is highly non-linear to the extent that Simpson's integration rule has to be used to find out the cumulative values of the expressions. Sometimes, the approximation of $exp(x)$ or $ln(x)$ or $(1/x)$ up to second-degree terms has to be taken. Also, such highly non-linear optimization problems are $NP - hard$, and it is difficult to find a closed-form solution. Sometimes, make simplifying assumptions for the ease of computation also. At times when the number of decision variables is very high, for example in case of pricing cum inventory dynamics, those situations shall use meta-heuristics for the solution. It is here that the genetic algorithms shall be deployed to yield the near-to-optimal solution faster and more efficiently. Genetic algorithms have a definite advantage in cases where there are multiple local optima, or where the objective function is not smooth (so derivative methods cannot be applied), or where the number of parameters is very large, or where the objective function is noisy or stochastic. GA does not require any information about the structure of the function to be optimized and uses it as Black Box, while Classical optimization methods should use some information. Random-search oriented optimization algorithms don't require information about the initial point and successfully find optimal solutions. Given the above merits of GA, a lot of research on inventory optimization has already used the genetic algorithms for computations.

This research shall not work on the ground level numbers because it is very important not to divulge publicly the information related to purchase costs, selling price, etc. that are confidential to the companies. Thus, there shall be no data collection in this research. It shall be fundamental research rather than applied research. However, to ensure the validity of the model and the findings, it shall consult the industry experts and logically verify the deliverables as well as the outcomes.