Diffusion of Multigenerational Technologies in the Indian Machine Tool Industry: Bass Model

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Abstract

Product sales and demand forecasting are crucial for future technological investments and technology strategy formulation. Forecasting technological diffusion plays a vital role in short and long-term product development planning. Extant literature has showcased the significance of diffusion modeling approaches in accurately predicting the production or sales of new products. The present study proposes forecasting the production trends of non-CNC and CNC-based metal-cutting machine tools in the Indian market. The study employs the Bass model to forecast the production of Turning and Milling machines introduced in the last five decades (1970-2019). The results demonstrate a decreasing production trend for non-CNC-based Lathes and Milling machines and an increasing trend for CNC-based Turning and Machining Centres. The study findings also highlight the co-existence of multiple technological generations and its impact on dynamic market demand trends. The study has implications for machine tool manufacturers in anticipating market demand and strategizing technology and product development planning.

Keywords
Forecasting, Technological diffusion, Bass model, Machine Tools, India.

1. Introduction

Increasing uncertainty and ambiguity have raised concerns and challenges for product manufacturers and R&D managers regarding future production and sales of units. However, multiple techniques and approaches have been identified in the literature for effective product planning and strategic decision-making. Extant literature has identified forecasting as an efficient technique for gauging technological diffusion and innovation (Kang et al. (1996), Kim et al. (2009), Cho and Diam (2016), Lee et al. (2017), Duwe et al. (2018), Heymann et al. (2021)). Petropoulos et al. (2022) systematically reviewed the theory and practice of forecasting. The forecasting technique, in general, is used to predict future values based on patterns identified from current and historical values. In the case of technological diffusion and innovation, forecasting is employed for strategic anticipation (Meade & Islam, (2006) Peres et al. (2010)). Forecasting is usually employed to gain insights into market demand trends or technology emergence to enhance competitive advantage. The findings from forecasting aid R&D managers in effective resource allocation, directing innovation efforts towards adopting key technologies for product development.

Diffusion and subsequent adoption of emerging and advanced technologies in new products can be measured using diffusion models. Forecasting methods are utilized to predict the future integration of emerging technologies into products and their consequential influence on markets, socio-economic factors, and technological systems. Among the fundamental and widely used diffusion models is the Bass Model, first introduced by Bass in 1969. Originally formulated for consumer marketing scenarios, this model will be further explored in the following sections.

The advent of Industry 4.0, automation, and advanced manufacturing technologies has brought about substantial technological transformations within the manufacturing sector. The machine tool industry, being the mother manufacturing industry, is affected by technological changes. Hence, it is imperative for industry practitioners to foresee plausible future changes and anticipate technological changes for effective implementation of the products. Forecasting technological changes provides key insights into industry transformation or technological evolution, affecting industry growth and competitiveness. Employing efficient forecasting techniques will facilitate informed decision-making by R&D managers and policymakers.

The Bass model describes the innovation phases from launch or introduction, growth, maturity, and decline. It provides insights into how innovations spread based on market potential and the adoption behaviors of innovators and imitators. This model helps us track the evolution of markets and how market participants respond to significant technological shifts. Technological change can be explained as a competitive process in which newer and more advanced technologies gradually replace older ones (Fisher and Pry, 1971). This force of technological change has a significant impact on markets characterized by high levels of innovation and dynamism. These changes often drive markets forward by increasing product complexity differentiation and introducing uncertainties in market niches. Technological improvements frequently create opportunities for new market niches, intensifying market competition (Lawless and Anderson, 1996).

The present study employs the Bass model as a forecasting technique to predict machine tool production in the Indian market. The study enhances understanding of technology diffusion and its impact on technology planning, product development, and decision-making. The study findings significantly add to technology diffusion and innovation management literature in the context of strategic industries like the Machine Tool Industry of India.

1.1 Technological Diffusion in the Indian Machine Tool Industry

The Indian machine tool (MT) industry has undergone significant transformation since its inception. A pivotal moment in its evolution came with the introduction of numerical control technology during the 1950s and 1960s, which brought about a revolution in the machine tool sector. Consequently, the industry experienced substantial growth during the 1960s and 1970s through collaborative product ventures. Figure 1. provides a concise overview of the key events and factors that have driven the evolution of the MT industry in India. Furthermore, the advent of microcomputer-based numerical control machine tools led to an exponential increase in the demand for MT. Sales of microcomputers-based NC machines grew commensurate with the processor market in the 1970s. However, Indian manufacturers lagged with the production of advanced machine tools. This period has witnessed multiple joint ventures between Indian and Japanese manufacturers to produce CNC machine tools and meet the demands of the end-user industries. In the 1980s, digital control was introduced for special machines in the industry. Hindustan Machine Tools (HMT), an Indian state-owned manufacturing company, developed its first CNC turning and machining centers in the 1980s.

Domestic manufacturers had a commanding hold on the Indian market, with a whopping 90% share in the early 1990s. New economic policy reforms or Liberalization, Privatization, and Globalization (LPG) reforms for the Open Market Economy were introduced by the Indian government in 1991. By 1992, all import barriers to machine tools were eliminated. The emergence of technocrat-driven private machine tool manufacturing firms was seen in the Indian market. Post-liberalization, the market share of public sector giants plummeted, while new medium-sized companies and foreign players entered the Indian market with fresh investments. Thus leading to a significant shift in the machine tool industry. Gradual growth characterized the Indian MT industry throughout the 1990s till the early 2000s. In the following decade, 2000-09, manufacturers commenced cautiously due to the aftermath of the 1998-2002 recession, leading to domestic demand fluctuations. Despite the initial setback, the industry witnessed a striking increase in demand from 2003 to 2007, driven by the booming expansion of the automotive and ancillary components industry. By the end of this decade, domestic manufacturers had lost their market share and was now reduced to 30%. Several domestic manufacturers joined hands to export machines. However, increasing domestic demand for highly efficient machine tools led to the stronghold of imports in the Indian market. With the increasing technological gap, the need for technological upgrading led to the Government of India (GoI) initiating a National Programme for Development of Machine Tool Industry (NPDMI) in September 2001.

In the subsequent decade, the industry's market share contracted further to 25%. This period was characterized by strategic endeavors to bridge technology gaps and combat dual-use technology denial. Policymakers introduced a number of initiatives, such as the *National Manufacturing Policy (2011), Make in India (2014), and the National Capital Goods Policy (2016)*. Investments were made by setting up toolrooms, personnel training, and infrastructure under the *Scheme on Enhancement of Competitiveness in the Indian Capital Goods Sector- Phase I*. Establishment of Tumakuru Machine Tool Park (TMTP) in 2018 facilitated component and ancillary manufacturers positioned in close vicinity.

The machine tool industry is primarily driven by its end-user industries. In recent years, sunshine sectors like electronics, semiconductors, renewables, and power have gained prominence as key strategic sectors for the nation's economic growth. Initiatives are focused on improving the technological competitiveness of domestic manufacturers to produce high-productivity, precision, and reliable machinery for the market. The Indian government introduced Amrit Kaal (or Era of Prosperity) initiatives in 2021 aimed at upgrading technology competitiveness (Figure 1).

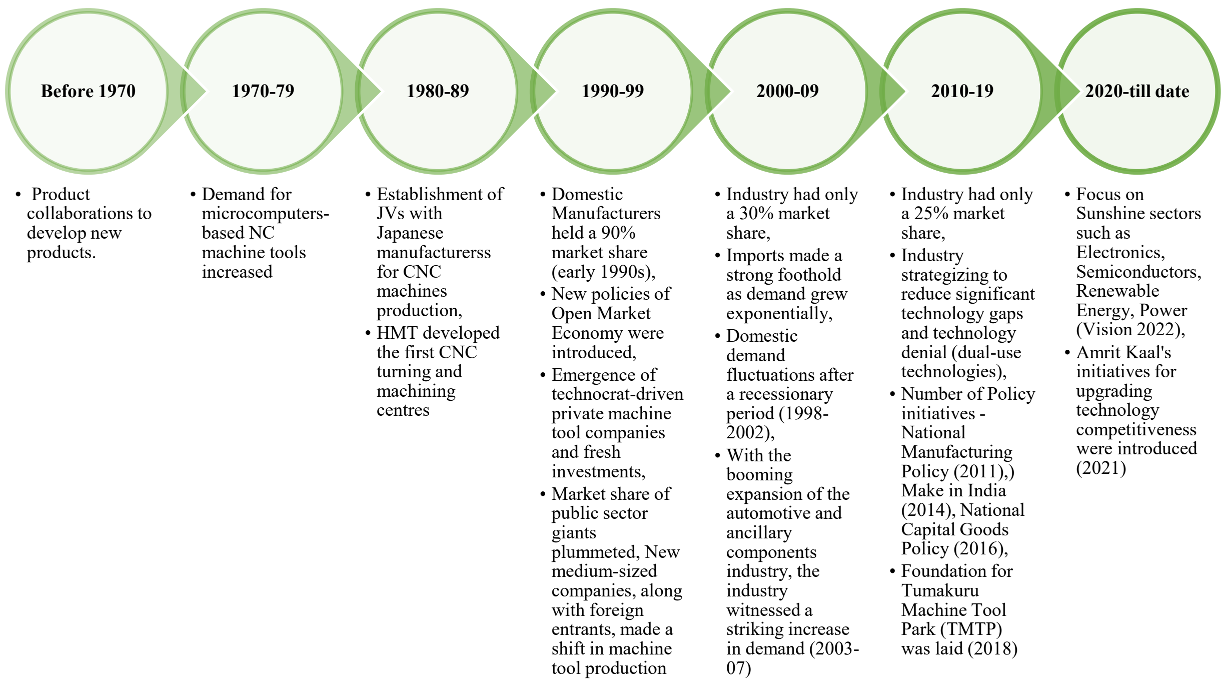

Figure 1. Technology evolution in the Indian Machine Tools Industry.
Source: Authors' Compilation from multiple industry and government reports.

1.2 Objectives

1. To forecast the production of metal cutting machine tools in the Indian market, particularly on Turning and Milling machines.

2. Utilizing the Bass model for analyzing the diffusion patterns of technological generations within machining technologies for the Indian MT industry.

3. To analyze the production trends of non-CNC and CNC-based Lathes, Milling machines, turning centres, and Machining Centres, taking into account the coefficients of innovation and imitation.

2. Theoretical Background

2.1 Modeling Technological Diffusion and Substitution

a. Technological diffusion

The diffusion of technology is a phenomenon that pertains to the proliferation of technological advancements across various industries or sectors, leading to continuous technological enhancements and widespread adoption by end-users or consumers. This rate of technological diffusion can be depicted by an S-shaped curve, illustrating the initial phase of technology introduction, followed by successful innovation and growth, resulting in increased market adoption and eventually tapering off as the technology reaches its maximum potential within a market (Katz and Levin, 1963).

Technological advancement or continuous improvement is brought by periods of incremental change. The continuity of older and new generations does not portray rapid or radical technological shifts in the industry. Technological advances may sometimes lead to disruptive innovations or technological convergence. The new generations of technology may not immediately sweep the preceding generations in the existing market. However, introducing new products utilizing advanced technologies will lead to price fluctuations and changes in market shares. The new technological generation may open new market niches and close existing ones. Market share or niche switching will reposition firms (Lawless and Anderson, 1996). The emergence of a new generation co-existing with the previous generation provides opportunities for firms to expand their offerings portfolio.

b. Technological substitution

The pace at which technology substitutes older generations is determined by shifts in market share between the two technologies. Market share, defined as the ratio of sales of the latest generation to total sales across generations, typically exhibits an S-shaped growth pattern, with Fisher and Pry (1971) proposing a substitution model based on competitive technological advancements and the proportional rate of substitution relative to the remaining older technology, known as Pearl's Law.

c. Combining technological diffusion and substitution

Diffusion models are designed to depict the adoption patterns and forecast the evolution of technologies, with Rogers' (1983) normal distribution-based categorization of adopters into innovators, early adopters, early majority, later majority, and laggards. Bass (1969) introduced a mathematical model for predicting demand growth in consumer durable products, taking into account external and internal influences labeling adopters as either innovators or imitators. The Bass model and its various adaptations have been widely embraced for forecasting purposes by institutions and corporations such as Kodak, IBM, and Hewlett-Packard.

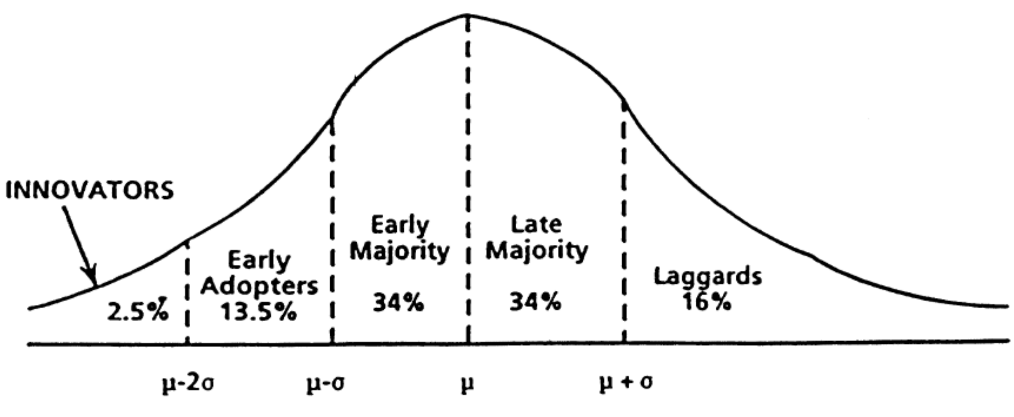

Figure 2. (a). Rogers' Adopters' Categories. **Source**: Mahajan et al. (1995)

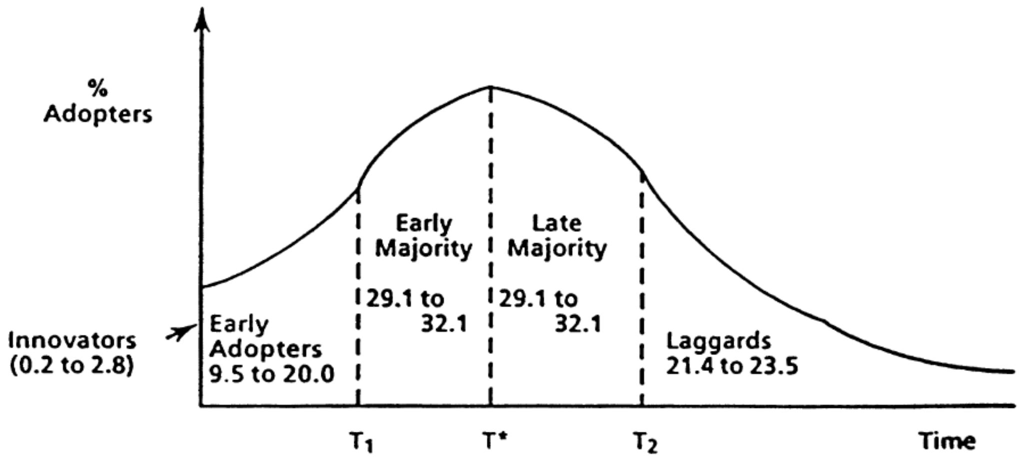

Figure 2. (b). Bass Adopters' Categories.
The adopters' percentage range is based on Bass's (1969) parameter estimation.

The Bass model emphasizes the timing of adoption and defines "f(t)" as the probability of adoption at time "t," with "F(t)" representing the fraction of ultimate potential adoption by that time. Norton and Bass (1987) introduced the coefficients "p" (innovation) and "q" (imitation), while in cases of multiple unit adoption, sales can be calculated as the product of the average units purchased per user per unit of time ("a") and the maximum potential users ("M"), denoted as "m." In this context, sales at time "t" can be estimated as "m" times "F(t)" as outlined by Norton and Bass in 1992.

2.2 Law of Capture

Norton and Bass (1992) made an empirical generalization called the *'Law of Capture,'* where advanced technological generations overtake the demand for products or services from previous generations via the process of adoption and diffusion. The end-users or consumers do not adopt new and advanced technologies as soon as they are introduced in the market, even though they seem lucrative. The industrial learning pace sets the tone for the diffusion process. The new products utilizing the latest technologies introduced in the market will substitute for the current products from previous generations or past technologies. The new products will improve quality, accuracy, precision, performance levels, and economic affordability. The new products may increase efficacy and efficiency levels by integrating multiple functions in a single product unit. However, sales of new products may not increase instantaneously and have a steady growth of early product variants. The pattern for products with earlier generations will soon face a decline. The diffusion pattern of four technological generations is described below and shown in Figure 3.

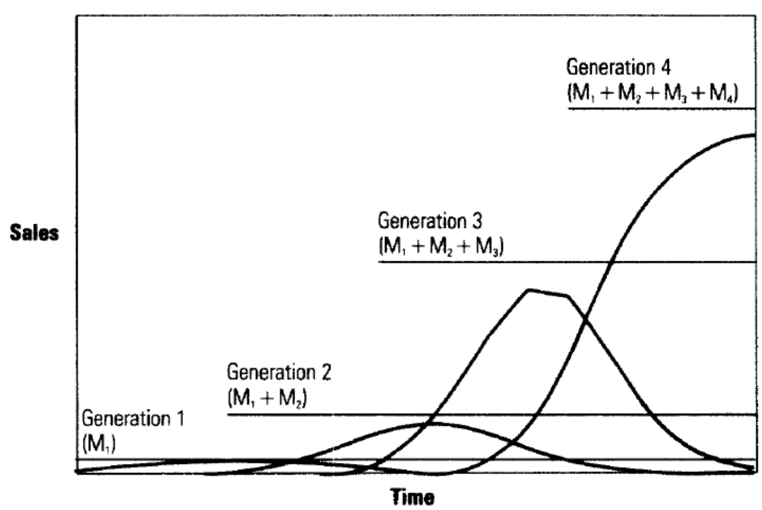

Figure 3. Growth and Diffusion Patterns for Technological Generations. **Source**: Norton and Bass (1992)

Sales are corelated to the cumulative distribution function of the adoption rate. However, the sales will vary while dealing with generations of products. Considering two generations of products, one part of the consumer will continue utilizing previous generations, and another will adopt the latest generation and move on with the next generation.

For three generations, sales at the time (t) will be

$S_{(1,t)} = F(t_1) * m_1 * [1 - F(t_2)]$

$S_{(2,t)} = F(t_2) * [m_2 + F(t_1) * m_1 * [1 - F(t_3)]$

$S_{(3,t)} = F(t_3) * [m_3 + F(t_2) * (m_2 + F(t_1) * m_1)]$

where, $S_{(i,t)}$ = Sales of i^{th} generation at time period t

t_i = time since the introduction of the i^{th} generation

m_i = incremental market potential for the i^{th} generation

$F(t_i)$ = Cumulative distribution function of the adoption rate

$F(t_i) = [1- e^{(-(p+q)t_i)}] / [1 + (q / p) * - e^{(-(p+q)t_i)}]$

The variables p and q determine the rate and shape of the growth curve described by $F(t_i)$, respectively (Norton and Bass (1992), Mahajan et al. (1995)).

2.3 Literature Review

Extant literature concerning the diffusion and adoption of technology employing the Bass model and its iterations in various industrial contexts is summarized below in Table 1.

Table 1. Summary of applications of Bass diffusion models and their variations in different industrial contexts.

S. No.	Author	Journal/ Conference	Model	Industry Focus	Applications	Region
1	Dodds (1973)	American Marketing Association	Bass model	Cable Television	Long term Forecasting	NA
2	Tigert and Farivar (1981)	American Marketing Association	Bass model and modified analog of the basic model	Optical Scanning Equipment sales data (1974-79)	Production scheduling and market development	USA
3	Srinivasan and Mason (1986)	Marketing Science	OLE, MLE, NLS – Bass model	Dishwashers	Reducing error anomalies	USA
4	Bretschneider and Bozeman (1986)	Technological Forecasting and Social Change	Adaptive Diffusion Model – (Bass-Mansfield Model)	Robotics (1970-85)	Dynamic models for forecasting	USA (New York)
5	Bass et al. (1994)	Marketing Science	Generalized Bass model	Color TV	Product Planning - Pricing and Advertising	USA
6	Hamoudia and Islam (2004)	Telektronnik	Diffusion Models	Wireless Messaging – SMS (1998-2003)	Forecasting market growth	Europe – 7 countries
7	Chen and Carrillo (2011)	European Journal of Operational Research	Modified for multi-functional products	Electronics (Printers & scanners)	Adoption, launch, and switching rate of fusion and single-function products	NA

8	Kim et al. (2009)	American Institute of Physics	Bass model	IPTV unit platform technology	Patent data-based technology forecasting	NA
9	Jiang and Jain (2012)	Management Science	Generalized Norton-Bass Model	Analog (1984-2006) and Digital (1985-2006) Cellular Subscriptions & DRAM sales data (1974-84)	Multigeneration product diffusion	USA
10	Qin and Nembhard (2012)	Int. J. Production Economics	Modeling PLC process - Geometric Brownian Motion (GBM) model	Semiconductor Manufacturing (DRAM sales data 1987-97)	Design strategies and dynamic production planning	NA
11	Liu et al. (2013)	SAE International	Modified Bass Model	Electric Vehicles Jan' 00-Apr'10	Scenario analysis	NA
12	Naseri and Elliot (2013)	Journal of Marketing Analytics	Bass, Logistic and Gompertz growth models	Online shopping (1998-2009)	Pre-launch forecasting	Australi a
13	Massiani and Gohs (2015)	Research in Transportation Economics	Bass model	Automotive technology (Electric Vehicles)	Parameter selection	German y
14	Jeong et al. (2015)	Journal of Engineering and Technology Management	Bass diffusion model	Mobile Communication technology	Patent road mapping	NA
15	Park and Choi (2016)	Technological Forecasting and Social Change	Continuous and Discrete Bass Models	Clothes Dryers, Room Air Conditioners, & Color TV	Valuation scheme of adopters	USA
16	Li et al. (2017)	Journal of Advanced Transportation	Modified Bass and Lotka-Volterra Model	Battery electric vehicles (BEV) Jan' 15-Sep'16	Short-Term Forecasting	China
17	Dong et al. (2017)	Technological Forecasting and Social Change	Time-series forecasting model, threshold heterogeneity diffusion model, Bass diffusion model, and NREL's dSolar model	Solar photovoltaic	Forecasting technological diffusion	USA (Califor nia)
18	Ganjeizadeh et al. (2017)	Procedia Manufacturing	Look-like analysis and Bass model	Responsive neurostimulation system (RNS)	Generate baseline market demand forecast with no historical data	NA
19	Oliinyk et al. (2018)	Journal of Applied Economic Sciences	Bass original and refined (Pontryagin maximum principle) model	Smartphones (2009-16) & computers (1996-2016)	Optimize product distribution forecasting process	NA
20	M.J. van der Kam et al. (2018)	Energy Research & Social Science	Regression + Bass model	Energy Sector - Solar Photovoltaic Systems and EV (2005-14)	Energy Transition strategies	Netherla nds

21	Abedi (2019)	Physica A	Compartmental diffusion model	Internet Broadband Services (2003-17)	Operation (supply chain) and marketing strategic planning	US, Canada & Mexico
22	Shi and Chumnumpan (2019)	European Journal of Operational Research	Genetic algorithm	Mobile Telecommunication services	Multi-brands and multigeneration product diffusion	Japanese
23	Grasman and Kornelis (2019)	Journal of Mathematics in Industry	Bass model and Stochastic extension	Steam Iron Sales	Parameters' validity and sensitivity for improved forecasting	NA
24	Ramírez-Hassan and Montoya-Blandón (2020)	Internal Journal of Forecasting	Bayesian estimation of Generalized Bass model	Compressed natural gas sales	Pre-Launch forecast	NA
25	Han et al. (2022)	Technological Forecasting and Social Change	Improved Bass models: Exponential- and Power-function models	Social Media - Microblogs	Product information diffusion	NA

Abbreviation: NA – Not Available.

3. Research Method

The present study proposes to show the diffusion of CNC-based MTs in the Indian context while considering the impact of the introduction of different generations.. CNC Lathes and Machining Centres are two prominent categories of CNC machine tools produced in India. Hence, these product families were selected for the applicability of the Bass model. The production data and year of introduction for two product families are tabulated below in Tables 2 and 3.

3.1 Bass Model

The Bass Diffusion model elucidates the adoption of new products, hinging on innovation and imitation factors. Frank Bass (1969) introduced it for sales forecasting, initially classifying adopters as innovators or imitators, later expanded by Rogers (1976) to include timing distinctions. The model assumes initial purchases by both groups, with innovator influence decreasing over time, encompassing coefficients for innovation (p) and imitation (q), while extensions consider variables like pricing and advertising (Bass et al., 1994).

3.2 Analysis Procedure

The MODEL procedure was carried out using the SAS software Version 9.4. The procedure involves solving simultaneous nonlinear equations for the technological generations using the SAS procedure for nonlinear Ordinary Least Squares (OLS) estimation. The impact of technology generations on the diffusion trend was studied.

4. Data Collection

The data was collected and compiled using annual reports of the Indian Machine Tool Manufacturers Association (IMTMA) from 1970-2019. Production data of Conventional Milling, CNC Milling, and CNC Machining Centres in the last five decades is summarized in Table 2. Production data of Non-CNC Lathes, CNC Lathes, and CNC Turning Centres in the last five decades is summarized in Table 3.

Table 2. Production of Conventional Milling, CNC Milling, and CNC Machining Centres in the last five decades (1970-2019). **Source**: IMTMA Annual Reports and Archives.

Year	**Generation I – Conventional Milling machines**	**Generation II – CNC Milling machines**	**Generation III – Machining Centres**
1970	655	-	-
1971	682	-	-
1972	632	-	-

1973	779	-	-
1974	813	-	-
1975	924	-	-
1976	948	-	-
1977	968	-	-
1978	983	-	-
1979	1239	-	-
1980	1032	-	-
1981	1163	-	-
1982	1140	-	-
1983	1112	-	8
1984	1161	-	7
1985	1173	-	28
1986	1254	6	50
1987	1388	4	73
1988	1064	8	48
1989	1263	17	96
1990	1451	23	105
1991	1309	26	126
1992	1095	23	145
1993	1049	20	98
1994	1269	20	45
1995	715	18	159
1996	644	16	112
1997	692	14	68
1998	453	67	122
1999	339	53	240
2000	296	86	229
2001	268	95	222
2002	172	94	325
2003	169	95	624
2004	237	101	856
2005	215	113	1075
2006	228	112	1267
2007	207	155	1289
2008	258	120	1402
2009	236	124	1414
2010	272	129	2024
2011	285	130	3585
2012	271	132	2459
2013	213	133	2900
2014	248	140	4480
2015	224	142	5980
2016	201	155	6969
2017	123	163	8868
2018	110	180	6884
2019	104	11	6262

Table 3. Production of Non-CNC Lathes, CNC Lathes, and CNC Turning Centres in the last five decades (1970-2019). **Source**: IMTMA Annual Reports and Archives.

Year	Generation I – Non- CNC lathes	Generation II – CNC Lathes	Generation III – CNC Turning Centres
1970	-	-	-
1971	5193	-	-
1972	4426	-	-
1973	3630	-	-
1974	4066	-	-

1975	5865	-	-
1976	5000	-	-
1977	4156	-	-
1978	4176	-	-
1979	4708	-	-
1980	6390	-	-
1981	5899	-	-
1982	5346	-	-
1983	5081	-	-
1984	4422	-	-
1985	4438	-	35
1986	4064	-	28
1987	3647	4	23
1988	3077	32	57
1989	3315	13	100
1990	3076	101	170
1991	2941	103	178
1992	2351	128	202
1993	1996	93	143
1994	1179	122	65
1995	815	100	181
1996	2674	497	196
1997	1790	590	210
1998	1112	513	225
1999	1659	376	239
2000	1210	564	254
2001	1063	644	269
2002	622	588	283
2003	341	782	298
2004	242	1197	313
2005	294	1809	327
2006	225	2293	342
2007	230	2318	328
2008	210	2310	356
2009	216	2478	427
2010	255	2,556	398
2011	246	4,492	433
2012	389	7,196	506
2013	345	4,548	528
2014	460	5,646	597
2015	266	7,266	636
2016	308	7,023	583
2017	243	11,982	593
2018	361	16,112	527
2019	367	17,798	682

4.1 Data Normalization and Parameter Estimation

A data normalization procedure is employed to make the data consistent for analysis. Normalization of data aids in comprehending the pattern effectively. However, it isn't easy to analyze all three variables simultaneously. Initially, two variables are modeled one after the other. Thus, the streamlined approach effectively models the two chosen variables, in contrast to the complexity introduced by the three variables. The data adjustment facilitated a more precise pattern identification and enhanced the model's performance. Parameters such as p, q, m1, m2, and m3 are integral to the nonlinear equations. The parameter values are estimated and converged within specified limits, which is crucial for the SAS modeling procedure. Furthermore, the parameters aid in forecasting production trends for machine tools, as tabulated below in Table 4.

Table 4. Summarized Values of Parameters

Product Category	Generation	Parameters	Standard Error	R^2
Milling Machines	Gen I - Conventional Milling machines	$p = 0.018$, $q = 0.174$, $m_1 = 0.426$, $m_2 = 0.342$	RMSE = (0.057 – 0.122), MSE = (0.003 – 0.0149), MAE = (0.033 – 0.364)	0.889
	Gen II - CNC Milling machines			
	Gen III - Machining Centres			
Lathes Machines	Gen I - Non-CNC Lathes	$p = 0.0062$, $q = 0.271$, $m_1 = 0.745$, $m_2 = 2.015$	RMSE = (0.073 – 0.608), MSE = (0.005 – 0.37), MAE = (0.041 – 0.54)	0.842
	Gen II - CNC Lathes			
	Gen III - CNC Turning Centres			

5. Results and Discussion

5.1 Results

Simple extrapolation of production data is usually employed for forecasting future production trends. However, this extrapolation does not account for technological generations and their impact on future production. Simple extrapolation may be misleading with a consistent increase in production across all the generations. In contrast, we obtained different results when we applied the Bass model, which incorporates generational effects. Specifically, the first two generations of milling units and the initial generation of lathes displayed declining production trends. However, lathe production stabilized during the second generation and then experienced an exponential surge in the third generation.

The increased demand for advanced or CNC-based machine tools has led to a significant increase in technological generations II and III compared to a decline of the first generation or non-CNC-based machine tools. Generation I or non-CNC-based Lathe and Milling machines have seen a decline in production due to low demand from end-users. Generation II – CNC Milling machines and Lathes have grown due to increased demand from end-user industries. Generation II has now reached saturation in the market. There has been a diffusion of CNC machining technologies in the Indian market. Domestic manufacturers have adopted CNC-based machining technologies and assimilated the technology in the Lathes and Milling machines. However, with the introduction of Industry 4.0, automation, and advanced manufacturing technologies, manufacturing systems now require a network of smart, intelligent, and well-connected advanced CNC machine tools on the shop floor. Generation III or CNC Machining and Turning centres will significantly increase production in the coming years due to the demand for integrated and intelligent machine tools on the shopfloor. There has been a gradual growth in the production of advanced CNC machining technologies attributed to the fact that domestic manufacturers are still adopting the technology and have not fully incorporated it into their products.

The findings from the Bass model highlight the impact of technological generations on demand and production trends. The results suggest that machine tool manufacturers should prioritize embracing technological advancements and incorporating the latest innovations into their products to sustain a competitive edge in the market. Accurate forecasting of technological progress can significantly impact manufacturers by enabling them to capture market share and enhance their technological competitiveness. The graphical representation captures the alignment between the actual and fitted production trend of conventional milling, CNC Milling, and CNC Machining Centres, as shown below in Figure 4. Fitted lines aid in better visualization of patterns or trends in the graph (Figure 4).

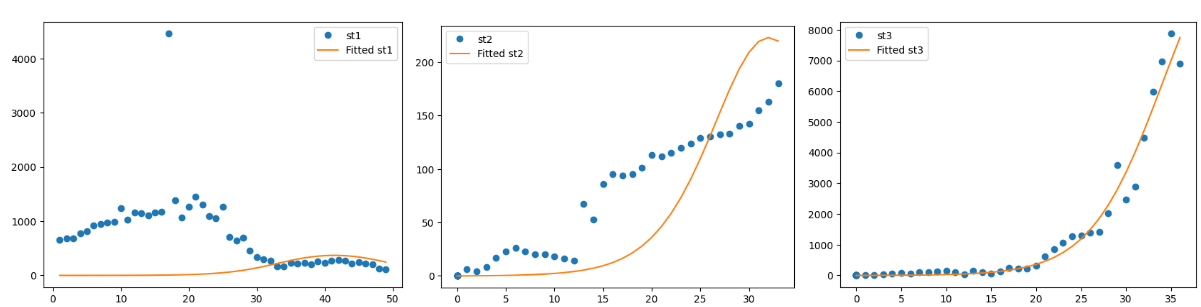

Figure 4. Actual and fitted production trend of Convectional Milling (Gen I), CNC Milling (Gen II), and CNC Machining Centres (Gen III). **Abbreviations**: st_1 = Actual Production of Generation I, st_2 = Actual Production of Generation II, st_3 = Actual Production of Generation III

There has been a significant shift from non-CNC to CNC machine tools in the MTs of India. There has been a steady decline in non-CNC Lathes and Milling machines in recent decades. There has been exponential growth in CNC Lathes and Milling machine production, showcasing diffusion and adoption of CNC machining technologies. There has been a gradual growth in the diffusion and adoption of advanced CNC machining technologies, leading to the production of CNC Machining and Turning Centres. Significant adoption of Generation II machine tools and slow adoption of Generation III is due to demand from end-user industries. While widespread adoption of CNC machining is seen among small and mid-size manufacturers, advanced CNC machining is adopted mostly by large manufacturers due to huge capital and infrastructure investments. Adopting advanced CNC machining technologies requires improved workforce skills and an interdisciplinary background to handle daily operations efficiently. The gradual adoption of advanced CNC and CNC machining technologies led to the existence of two technological generations in the Indian market. The co-existence of multiple technology generations portrays the technological capabilities and competitiveness of the manufacturers and industry. The graphical representation captures the alignment between actual and fitted production of Non-CNC and CNC Lathes and CNC Turning Centres, as shown below in Figure 5. Fitted lines aid in better visualization of patterns or trends in the graph (Figure 5).

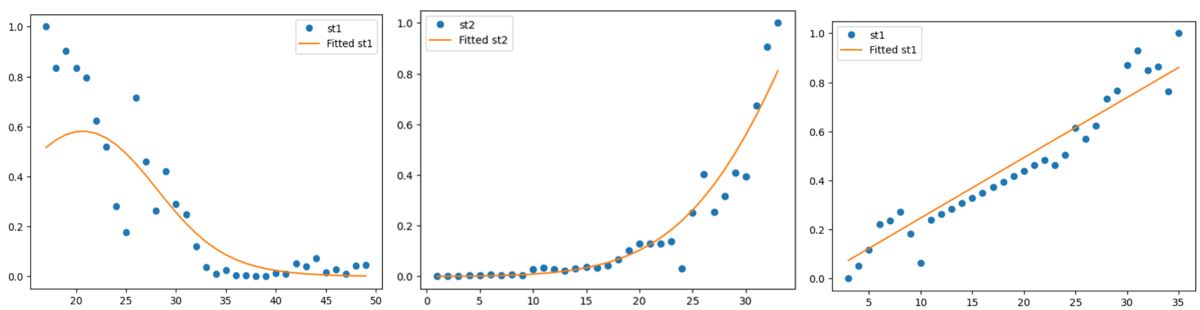

Figure 5. Actual and fitted production trend of Non-CNC Lathes (Gen I), CNC Lathes (Gen II), and CNC Turning Centres (Gen III). **Abbreviations**: st_1 = Actual Production of Generation I, st_2 = Actual Production of Generation II, st_3 = Actual Production of Generation III

The Law of Capture defines how demand for emerging technological generations eventually overtakes the market from previous generations. The Generation II incorporated in CNC Lathes and Milling machines offers improved performance compared to non-CNC machinery. On the other hand, generation III or advanced machining technologies incorporated in CNC Machining and Turning Centres offer enhanced performance. CNC Machining and Turning Centres machining on workpieces with reduced machining time, improved performance, enhanced productivity, and increased reliability. The newer generation offers interoperability, automation, and enhanced machining facilities for machine tools operating in a manufacturing system (Table 5).

Table 5. Forecasted Production values of Conventional Milling, CNC Milling, and CNC Machining Centres for the next decade (2020-29)

Year	Conventional Milling machines	CNC Milling machines	Machining Centres
2020	101	11	6564
2021	98	10	6864
2022	95	10	7160
2023	92	10	7451
2024	89	10	7738
2025	86	9	8019
2026	83	9	8295
2027	80	9	8563
2028	77	8	8825
2029	75	8	8921

Table 6. Forecasted Production values of Non-CNC Lathes, CNC Lathes, and CNC Turning Centres for the next decade (2020-29)

Year	Non- CNC lathes	CNC Lathes	CNC Turning Centres
2020	421	21536	1211
2021	390	26302	1479
2022	360	32121	1806
2023	333	39225	2205
2024	308	47896	2691
2025	285	58481	3284
2026	264	71399	4007
2027	244	87163	4889
2028	226	106398	5962
2029	209	129861	7270

Tables 6 showcases forecasted production values for machine tools for the coming years (2020-29). Increasing demand for advanced CNC machining technologies by automotive, aerospace, defense, electronics (PCB manufacturers), semiconductors, and power (Solar PV, Wind energy) sectors because they offer:

(a) increased productivity,
(b) enhanced reliability,
(c) improved precision,
(d) multiple complex machining operations on workpieces,
(e) reduced machining time,
(f) reduced downtime and errors, and
(g) predictive maintenance

With increased financial incentives and policy initiatives, major roadblocks of enormous capital and infrastructure investment will be eliminated for small and medium-sized manufacturers, enabling quicker adoption of advanced technological generations. Increased setting up of mini-tool rooms and training centers will facilitate workforce reskilling and training in advanced manufacturing, Industry 4.0, and automation technologies.

5.2 Findings

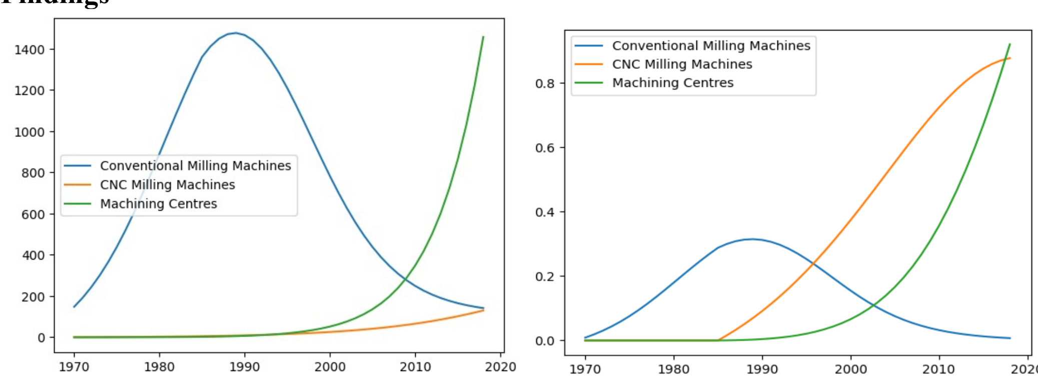

Figure 6. Diffusion of Technological Generations of Convectional and CNC Milling, CNC Machining Centres

The Norton-Bass model has been employed to forecast the demand for three generations of lathe and milling machines manufactured in India. The model captures the historical production of machine tools to predict trends for the next decade (2020-29). The forecast values for the years 2020, 2021, and 2022 are in agreement with the actual figures. The graphical representation also reveals the model's accuracy in fitting the past production trends of Machine Tools. It's important to note that the Figure 6 has been normalized, potentially resulting in a disproportionate representation. Figure 7. showcases the increasing production trends in CNC turning centers, albeit in small volumes, which mirrors the increasing production of machining centers in Figure 6. However, it's crucial to bear in mind that the normalized representation in the Figure 7 might not accurately reflect the actual magnitude of this growth. Figure 6 and 7. portray production trends of the technological generation of machine tools product families, namely, Lathes and Milling machines.

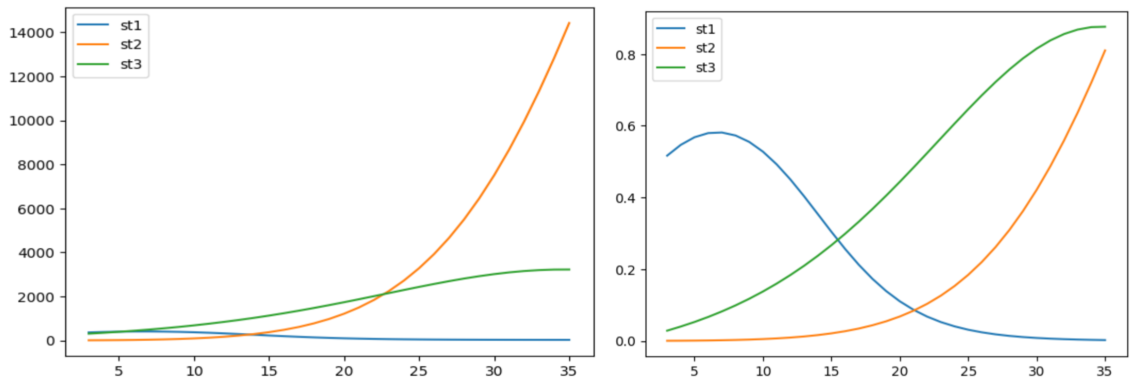

Figure 7. Diffusion of Technological Generations of Non-CNC and CNC Lathes and CNC Turning Centres

Innovation quotient (p): A low value of p suggests that the initial group of innovators who adopt a new technology right away is relatively small. In other words, only a small percentage of the population is eager to embrace new technologies immediately upon their introduction. Domestic manufacturers' slow adoption of advanced CNC machining technologies is due to a lack of capital investment, infrastructure facilities, and skilled workforce availability. The risk of early adoption of advanced machining technologies is amplified due to the high upfront cost and availability of end-user demands.

Imitation quotient (q): A low value of q indicates that the rate of imitation among the larger population is low. Lack of reverse engineering of machinery leading to imitating advanced machine tools further lowers the imitation rate. Unlike foreign manufacturers, domestic manufacturers did not readily adopt or imitate the advanced CNC machining technologies, which further led to gradual adoption.

Both low values of p and q together imply a slower and more gradual adoption process. As a smaller group, innovators set the initial pace of adoption, and their influence on imitators is limited. The technology takes time to gain momentum and reach a wider audience. The domestic manufacturers and end-user industries were reluctant to adopt advanced technologies as they accrue additional expenses (capital investment) and infrastructure facilities to accommodate advanced machinery.

5.3 Proposed Improvements

Bass model is a quantitative analysis that aids in comprehending the diffusion of technological innovations. However, inputs from industry practitioners, end-users, and machine tool manufacturers will add valuable insights into technological diffusion and adoption rate. Digging deeper into the impact of policy initiatives, financial incentives, and industrial policy reforms pertaining to geographic areas will enable a better understanding of technological diffusion.

5.4 Theoretical/Research Implications

The study is an attempt to investigate the technological diffusion and adoption of new products in the context of the Indian manufacturing industry. The research paper makes significant theoretical contributions by deepening our understanding of technological diffusion and substitution within the machine tool industry. The research study adds to the existing literature on diffusion-based modeling approaches. The empirical investigation of future production trends provides in-depth insights into the impact of technological generation diffusion on market dynamics. The analysis finds significance in comprehending technological diffusion and substitution in the context of the Indian machine tools industry. The model demonstrates the impact of political, technological, or other PESTLE factors affecting the diffusion, substitution, and adoption of machining technology. The study aids in comprehending technological evolution, leading to effective macro and micro-level technology management. The historical analysis of technological generation uncovers transformation in industry and market dynamics,

5. 5 Managerial Implications

The diffusion modeling approach assists R&D managers in strategizing and formulating new product development planning. The anticipation of production trends provides key actionable insights into future market trends and, thus, enhances firms' competitive advantage. Additionally, the model aids in demand forecasting for new products, facilitating informed production and inventory management. The study findings have significance in identifying technology obsolescence, forecasting new product introduction, and effective demand management. The study has implications for R&D managers anticipating market demand trends and aligning business goals/objectives for adopting future machining technological generations such as 3D or Additive Manufacturing, Digital Twins, and CPS.

6. Conclusion

Forecasting technological diffusion and adoption is significant for strategizing technology planning and product development. Technological competitiveness and development affect technological diffusion and adoption of advanced and emerging technologies. The current research aims to forecast production trends for two major product families – Lathes-Turning Centres and Milling-Machining Centres in the context of the Indian market. The study employed the Bass model to investigate technological generational diffusion patterns in machining technologies. The Bass model effectively captures the synergy among market potential, innovators, and imitators. The findings from the Bass model showcase a declining trend for the older technological generation and an increasing trend for new and advanced technological generations. In addition, the study highlights the co-existence of multiple technological generations. The study has implications for machine tool manufacturers in anticipating future market demand and strategic technology planning.

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