Short Project Report

Forecasting Bangladesh RMG Exports

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Summary

This report investigates the future of Ready-Made Garments (RMG) export performance of Bangladesh up to the year 2030 using multiple forecasting approaches, such as, **Linear Regression**, **Fisher–Pry Model**, **Gompertz Model**, **Floyd Model**, **Adaptive Weighted Smoothing**, and **Scenario Analysis**. Key results indicate that while RMG exports are expected to grow steadily by 2030, external factors such as international tariffs, geopolitical conflicts, and global economic recovery will strongly influence the trajectory. Scenario analysis suggests that Bangladesh may benefit from competitors' higher tariffs but faces risks from potential sectoral maturity and overdependence on RMG.

Acknowledgment

First and foremost, I would like to express my sincere gratitude to **Professor Iftekhar Uddin Bhuiyan**, our respected course instructor, for his valuable guidance, support, and encouragement throughout the project. His advice on both the technical aspects and broader implications of forecasting has been instrumental.

I would also like to thank **Manzila Islam Tuheen Ma'am**, who kindly organized an industrial tour to **Arbella Fashions Ltd.**, a leading RMG company engaged in export activities. The visit provided valuable insights into the operational, economic, and policy aspects of the RMG sector, which greatly enriched this project.

Table of Content

Introduction

The Ready-Made Garment (RMG) sector is the backbone of Bangladesh's economy, accounting for approximately 80% of total export earnings in the last decade (BGMEA, 2024) [1]. This sector employs millions of workers and is central to Bangladesh's industrial growth and international trade competitiveness. With a global shift in textile supply chains, Bangladesh has become the second-largest apparel exporter in the world after China (World Trade Organization, 2024) [2].

Historically, the growth of the RMG sector has gone through several phases. To illustrate this timeline, the following table is reproduced from Mondal, Uddin, and Akter (2024) [3],

Year	Matters
1970–1980	Initial stages of growth
1982–1985	Thriving days
1985	Initial quota restriction
1985–1990	The Knitwear sector developed significantly
1993	Child labour problem and new law of child labour
2003	Withdrawal of Canadian quota restriction
2005	Phase out of Export Quota System (Multi-Fiber Agreement)
2006	Protest by garments labour
2007–2008	Stable growth
2008–2012	Continuous progress
2012	Tazreen Fashion Factory fire
2013	Rana Plaza collapse; GSP suspended
2016	Holey Artisan Attack
2018	Implementing sustainability
2020	COVID-19 pandemic effect

This historical perspective highlights the sector's resilience. Despite serious setbacks (Rana Plaza collapse, GSP suspension, global pandemics), the RMG industry has continued to grow and dominate Bangladesh's export portfolio. However, being highly concentrated in one sector also poses risks.

Forecasting RMG exports to 2030 is crucial for understanding Bangladesh's future economic trajectory. To achieve this, multiple quantitative forecasting techniques are applied in this report, alongside qualitative scenario analysis to incorporate geopolitical and trade uncertainties.

Research Methods, Approaches, and Resources

2.1 Data Source (BGMEA)

The dataset used for this project is taken from the official BGMEA Export Performance, covering 1983–2024. [1]. The data is attached to Appendix A.

2.2 Linear Regression [4]

We model RMG exports (Y) as a linear function of time (X):

Model: $Y_t = a + bX_t$

Where,

'a' is the intercept, can be calculated by a = $\bar{Y}$ - b * $\bar{X}$

'b' is the slope estimated using least squares by $b = \frac{\Sigma(xi*yi)}{\Sigma(xi^2)}$

The regression gives a baseline growth trajectory and provides prediction intervals.

Calculated using MATLAB, Linear Regression Equation: Y=-2469037.91 + 1240.61 * X

Predicted RMG Export in 2030: 49401 million USD

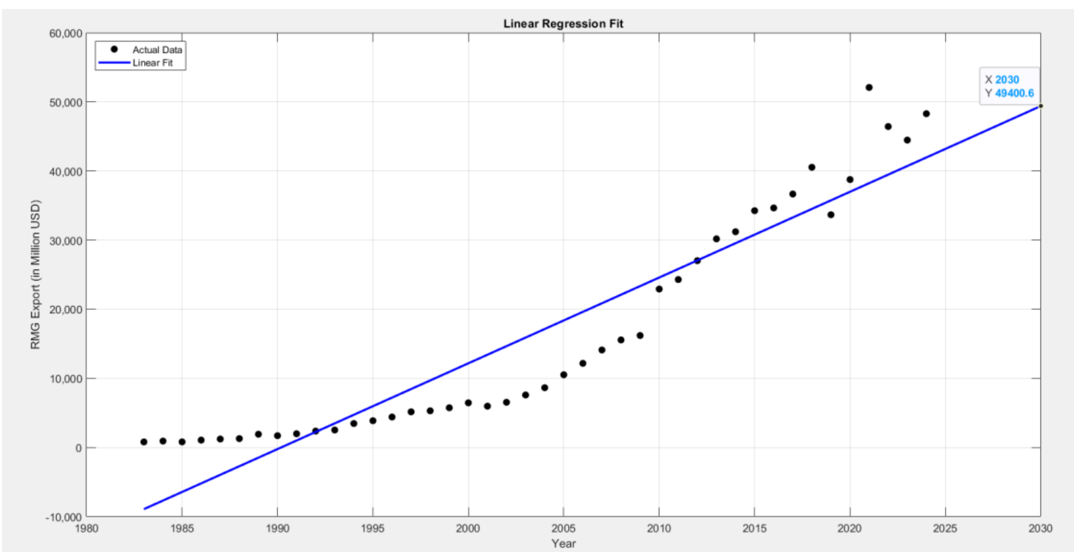

Figure 1: Linear Regression Fit for RMG Export till 2030

Coefficient of Determination, $R^2 = \frac{\sum_{i=1}^{n}(\hat{Y}-\bar{Y})^2}{\sum_{i=1}^{n}(Yi-\bar{Y})^2}$

Calculated using Matlab, $\boldsymbol{R^2 = 0.8778}$

90% prediction interval, $C.I. = \pm\left(t_{\frac{\alpha}{2},d.f.}\right)\sqrt{S_e^2\left(1+\frac{1}{n}+\frac{(X_* - \bar{X})^2}{\sum \mathbf{xi}^2}\right)}$

Calculated using Matlab,) 90% Confidence Interval for 2030 Forecast: **[39075, 59727]**

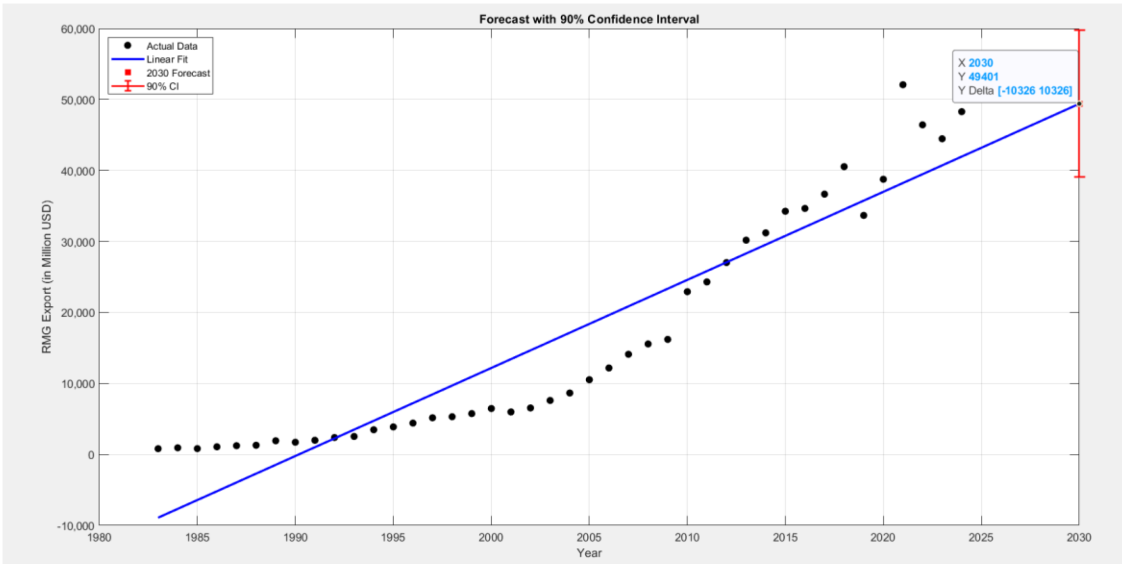

Figure 2: 90% Confidence Interval for RMG Export till 2030

2.3 Fisher–Pry Model [4]

The Fisher–Pry model expresses technological diffusion and market share growth as

Transformation: Zt= $ln\frac{L-Y}{Y} = lnc - bt$

Back-transform: $ln\frac{L-Y}{Y} = Z_t$

$\Rightarrow \frac{L-Y}{Y} = \exp(Z_t)$

$\Rightarrow L-Y = Y^* \exp(Z_t)$

$\Rightarrow L = Y(\exp(Z_t)+1)$

$\Rightarrow Y_{FP} = L/(\exp(Z_t)+1)$

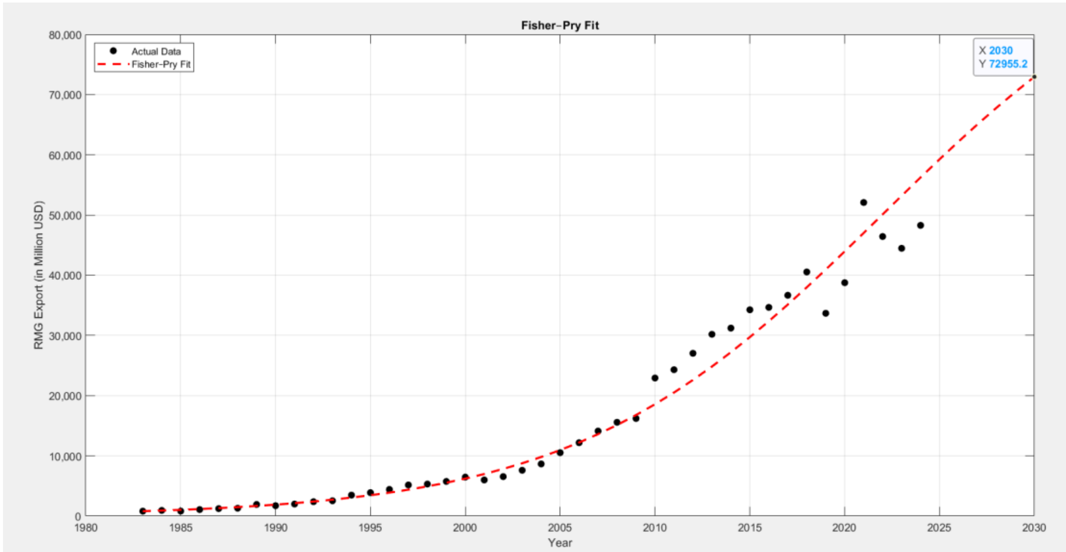

Figure 3: Fisher-Pry Fit for RMG Export till 2030

With **L = 100,000**, the **2030 forecast** is **72,955** million USD.

2.4 Gompertz Model [4]

The Gompertz model is another S-curve but with asymmetric growth:

Transformation: $\ln\left[-\ln\left(\frac{Y}{L}\right)\right] = Zg = \ln b - kt$

Back-transform: $\ln\left[-\ln\left(\frac{Y}{L}\right)\right] = Zg$

$$\Rightarrow \ln(Y/L) = -\exp(Z_g)$$

$$\Rightarrow Y_g = L^*\exp[-\exp(Z_g)]$$

It models early rapid growth followed by long maturity phases.

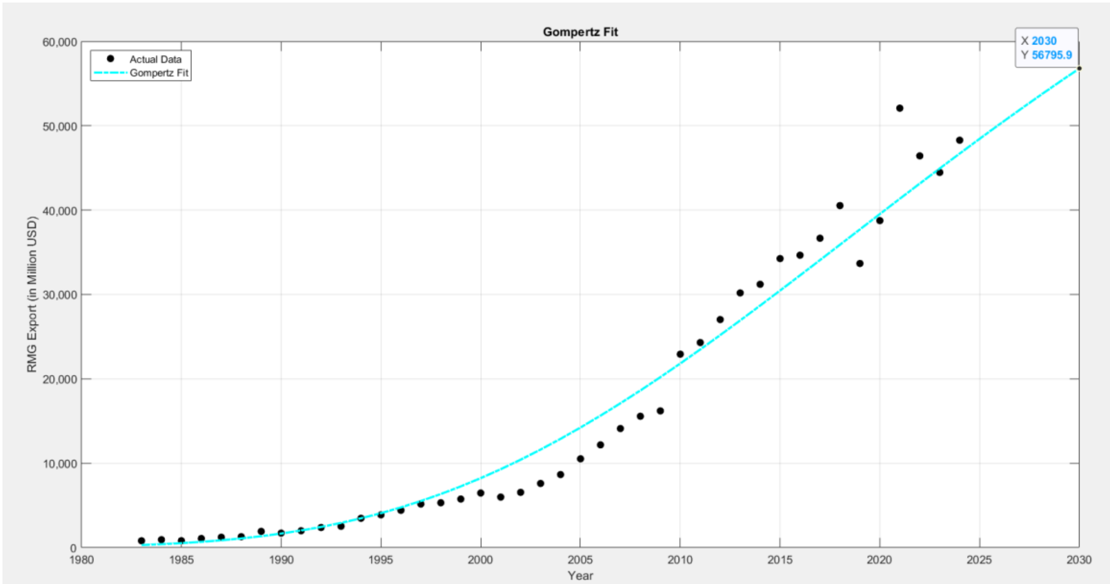

Figure 4: Gompertz Fit for RMG Export till 2030

With **L =100,000**, the **2030 forecast** is **56,796** million USD.

2.5 Floyd Model [4]

Floyd's transformation (from lecture):

$$S(Y) \equiv \frac{L}{L-Y} + \ln\left(\frac{Y}{L-Y}\right) = a + bt$$

To solve for (Y), we invert using the **Lambert W function**

Derivation (step-by-step inversion to Y):

1. Let $u=\frac{Y}{L-Y} \Rightarrow Y=\frac{Lu}{1+u}$ and, $\frac{L}{L-Y} = 1 + u$
2. Substitute into S: (1+u) + lnu = s = a+bt.
3. Rearrange: lnu+u = s-1
4. Exponentiate both sides: $e^{lnu+u} = e^{s-1} \Rightarrow ue^{u} = e^{s-1}$
5. By definition of **Lambert-W**, W(z) $e^{W(z)}$= z $\Rightarrow u = W(e^{s-1})$
6. Back-substitute:

$$Y = \frac{LW(e^{a+bt-1})}{1+W(e^{a+bt-1})}$$

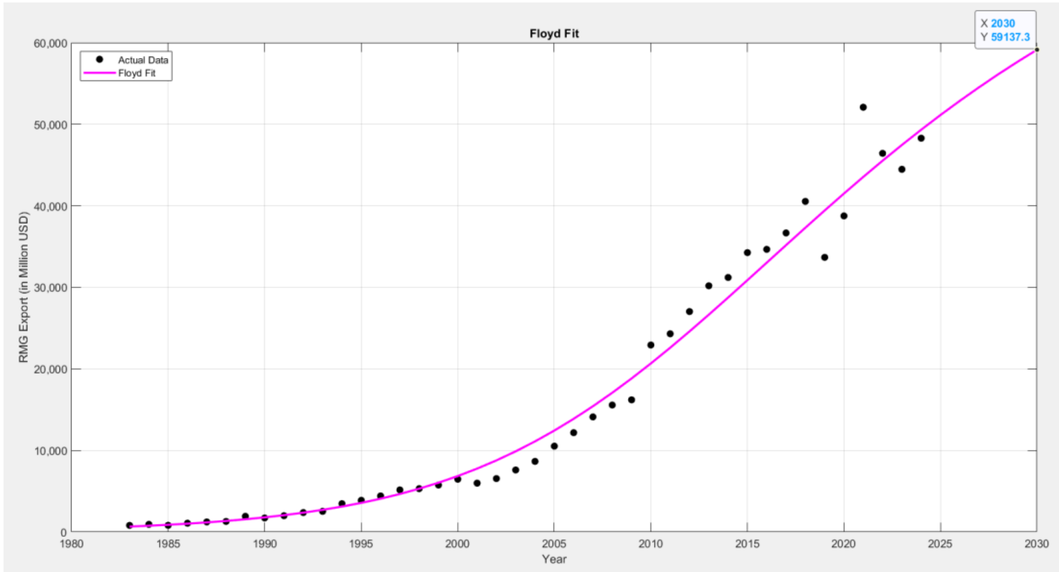

Figure 5: Floyd Fit for RMG Export till 2030

With **L =100,000**, the **2030 forecast** is **59,137** million USD.

2.6 Adaptive Weighted Smoothing [4]

We use the weighted smoothing formula:

$$X_{t+1} = \sum_{i=0}^{m} w_{t-i} X_{t-i}, \quad w_{t-i} = \frac{a(1-a)^i}{d}$$

where a is a smoothing parameter and d ensures normalization.

Derivation of d:

Weights must sum to 1:

$$d = \sum_{i=1}^{m} a(1-a)^i$$

This is a finite geometric series:

$$d = a(1-a)\frac{1-(1-a)^m}{1-(1-a)}$$

$$d = (1-a)(1-(1-a)^m)$$

This normalization ensures the weights add up to 1.

We try all values of a (0.01 to 0.99) and forecast for 2030. This gives a **range** of possible forecasts instead of a single number, making the method more robust.

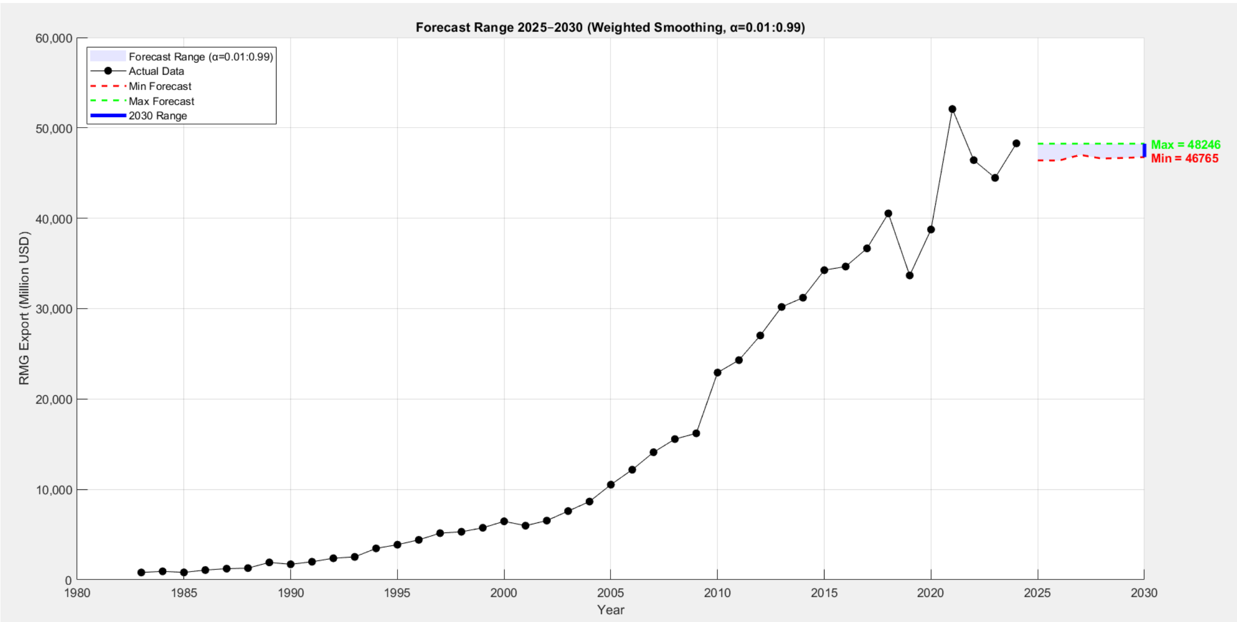

Figure 6: Adaptive Weight Smoothing

The range of forecasts for the year 2030 is from **46,765** to **48,246**.

2.7 Scenario Analysis [4]

The trajectory of Bangladesh's RMG exports is influenced not only by demand and production capacity but also by global political and trade policy changes. While quantitative models provide forecasts, scenario analysis adds depth by accounting for potential opportunities and risks.

1. Best-Case Scenario: Tariff Advantage and Peace Dividend

Earlier this month, the United States imposed an additional **25 percent tariff on Indian goods**, raising effective duties to as high as **50 percent**. Since India and Bangladesh export many similar RMG products—shirts, trousers, T-shirts, jackets, and accessories—this tariff creates a **rare opportunity for Bangladesh**. Buyers already signaled order cancellations in India, and some international companies (such as Pearl Global, sourcing for Gap and Collar) are relocating production to Bangladesh, Vietnam, and Indonesia to bypass steep Indian tariffs. [5]

If Bangladesh can capitalize on this moment—by improving technological capabilities, reducing dependence on imported yarn, and investing in automation—its **market share in the US** may expand significantly. In addition, the **peace dividend** from a resolution of the Russia–Ukraine conflict would stabilize energy and logistics costs, further boosting export performance. Under this optimistic scenario, RMG exports could exceed our baseline S-curve forecasts and surpass **USD 80 billion by 2030**, securing Bangladesh's dominance in global apparel.

2. Base-Case Scenario: Stable Growth Amid Competition

Bangladesh already commands nearly **80–84% of total national export earnings from RMG**. With stable policies, moderate improvements in technology, and continued labour cost advantages, the country is expected to maintain steady growth. However, the relative advantage from India's tariffs will not be exclusive—other competitors such as **Vietnam, Cambodia, and Indonesia** will also benefit. [5]

Furthermore, Bangladesh still faces structural issues: dependency on imported raw materials, limited design capacity, and infrastructure bottlenecks. In this base case, RMG exports continue to rise but largely within the range predicted by our **trend regression, Fisher–Pry, and Gompertz models** (around **USD 70–75 billion by 2030**).

3. Worst-Case Scenario: Regional Instability and Market Saturation

Several risks could push Bangladesh off track. First, an **India–Pakistan conflict** could destabilize South Asia, disrupt supply chains and reduce investor confidence. Second, if the **Russia–Ukraine war prolongs**, inflationary pressure may weaken Western demand for clothing, directly impacting orders. Third, **US tariff flexibility** introduces uncertainty: while India faces high tariffs now, future negotiations could reduce duties, diminishing Bangladesh's advantage. At the same time, **China**, currently facing tariffs around **55%**, might secure a better deal, reclaiming its dominance in the US apparel market. [5]

Bangladesh's **heavy reliance on RMG** also poses saturation risk. If diversification into jute, shrimp, or emerging export sectors fails, Bangladesh may struggle to maintain its export earnings. Under this scenario, RMG exports could stagnate or even decline after 2030.

These scenarios are not modelled numerically but included to add realism to the forecast range.

Results and Discussion

- **Linear Regression** predicts steady growth, with a forecast of ~(X) billion USD in 2030 but limited by assumption of constant trend.

  (a) Linear Regression Equation: **Y=-2469037.91 + 1240.61 * X**

  (b) Coefficient of Determination: **(R^2) = 0.8778**

  (c) Predicted RMG Export in 2030: **49401 million USD**

  (d) 90% Confidence Interval for 2030 Forecast: **[39075, 59727]**

- **Fisher–Pry and Gompertz** show S-curve stabilization,

  (a) Fisher-Pry: Predicted RMG Export in 2030: **72,955 million USD**

  (b) Gompertz: Predicted RMG Export in 2030: **56,796 million USD**

- **Floyd Model** captures asymmetric growth, giving slightly higher mid-term predictions.

  (a) Floyd: Predicted RMG Export in 2030: **59,137 million USD**

- **Adaptive Weighted Smoothing** provides a range of outcomes depending on 'a', giving flexibility in short-term forecasting.

  (a) Predicted RMG Export in 2030: from **46,765 million USD** to **48,246 million USD**

- **Scenario Analysis**

  - **Best case:** Bangladesh leverages tariffs + peace dividend → exceeds forecasts
  - **Base case:** Stable but competitive → matches baseline forecasts
  - **Worst case:** War, competition, or tariff reversals → stagnation or decline.

Conclusions

- Bangladesh's RMG sector is forecasted to remain the **dominant export sector through 2030**.
- Linear and S-curve models predict continued growth, but saturation signs exist
- Adaptive Weighted Smoothing offers a flexible forecasting envelope.
- Scenario analysis indicates opportunities and risks.

Further Research

Future work should analyze **RMG share of total exports**. Currently ~80% of Bangladesh's export earnings come from RMG. While stable, this reflects **sectoral maturity**, suggesting diversification is necessary. Applying S-curve theory, RMG may decline, and other sectors like **jute, shrimp, IT, or leather** could play an increasing role in the upcoming decades.

This research could include:

- Trend analysis of RMG share vs. other sectors.
- Forecasting scenarios where non-RMG exports grow.
- Policy implications for diversification.

References

1. BGMEA. *Export Performance Data (1983–2024)*. Link
2. World Trade Organization (WTO) data for 2024. Link
3. Mondal, M. S. A., Uddin, M. M., & Akter, N. (2024). *The Textile Industry in Bangladesh: Growth Trends, Challenges, and Future Prospects*. ResearchGate. Link
4. Roper, A.T. et al. (2011). *Forecasting and Management of Technology*. John Wiley & Sons, 2nd edition, 2011. Link
5. US tariffs on India: A rare opportunity Bangladesh cannot miss. Link

Appendices

A. Comparative Statement on Export of RMG & Total Export of Bangladesh

Value in Million USD (Fiscal Year Basis)

Year	Export of RMG	Total Export of Bangladesh	% of RMG's to Total Export
1983-84	31.57	811.00	3.89
1984-85	116.20	934.43	12.44
1985-86	131.48	819.21	16.05
1986-87	298.67	1076.61	27.74
1987-88	433.92	1231.20	35.24
1988-89	471.09	1291.56	36.47
1989-90	624.16	1923.70	32.45
1990-91	866.82	1717.55	50.47
1991-92	1182.57	1993.90	59.31
1992-93	1445.02	2382.89	60.64
1993-94	1555.79	2533.90	61.40
1994-95	2228.35	3472.56	64.17
1995-96	2547.13	3882.42	65.61
1996-97	3001.25	4418.28	67.93
1997-98	3781.94	5161.20	73.28
1998-99	4019.98	5312.86	75.67
1999-00	4349.41	5752.20	75.61
2000-01	4859.83	6467.30	75.14
2001-02	4583.75	5986.09	76.57
2002-03	4912.09	6548.44	75.01
2003-04	5686.09	7602.99	74.79

2004-05	6417.67	8654.52	74.15
2005-06	7900.80	10526.16	75.06
2006-07	9211.23	12177.86	75.64
2007-08	10699.80	14110.80	75.83
2008-09	12347.77	15565.19	79.33
2009-10	12496.72	16204.65	77.12
2010-11	17914.46	22924.38	78.15
2011-12	19089.73	24301.90	78.55
2012-13	21515.73	27027.36	79.61
2013-14	24491.88	30186.62	81.13
2014-15	25491.40	31208.94	81.68
2015-16	28094.16	34257.18	82.01
2016-17	28149.84	34655.90	81.23
2017-18	30614.76	36668.17	83.49
2018-19	34133.27	40535.04	84.21
2019-20	27949.19	33674.09	83.00
2020-21	31456.73	38758.31	81.16
2021-22	42613.15	52082.66	81.82
2022-23	38142.10	46430.71	82.15
2023-24	36151.31	44469.74	81.29
2024-25	39346.97	48283.93	81.49

B. MATLAB codes for Linear Regression, Fisher–Pry, Gompertz, Floyd, and Adaptive Weighted Smoothing.

a) Linear Regression, Fisher–Pry, Gompertz, Floyd

```
clear
close all
clc
%% RMG Export of Bangladesh (in Million USD), 1983-2024
X = (1983:2024)';
Y = [ 811;934.43;819.21;1076.61;1231.2;1291.56;1923.7;1717.55;
1993.9;2382.89;2533.9;3472.56;3882.42;4418.28;5161.2;5312.86;
5752.2;6467.3;5986.09;6548.44;7602.99;8654.52;10526.16;
12177.86;14110.8;15565.19;16204.65;22924.38;24301.9;
27027.36;30186.62;31208.94;34257.18;34655.9;
36668.17;40535.04;33674.09;38758.31;
52082.66;46430.71;44469.74;48283.93];

n = numel(X);

%% ----------- Linear regression ------------------
Xbar = mean(X);
Ybar = mean(Y);
xi = X - Xbar;
yi = Y - Ybar;

for i=1:n
    xx(i) = xi(i).^2;
    xy(i) = xi(i) .* yi(i);
end
sx = sum(xx);
sy = sum(xy);

b = sy/sx;
a = Ybar - (b.*Xbar);

Yhat = a + b*X;

for i=1:n
    yy(i) = (Y(i) - Yhat(i)) .^2 ;
end
Syy = sum(yy);

SE2 = Syy/(n-2);
R2 = (sum((Yhat - Ybar).^2))/ (sum((Y - Ybar).^2));

Xstar = 2030; %predicton year
Ystar = round (a + b*Xstar);

alpha = (1-0.90)/2; % 90% confidence interval
df = n-2;
tvalue = tinv(1-alpha, df);

CI = round (tvalue.* sqrt(SE2.* (1+(1/n)+(((Xstar-Xbar).^2)/sx))));

%% -----------------Fisher Pry--------------------
L= 100000; %(Upper Limit)
```

```
Ti= xi;
STi= sx;
Tbar= Xbar;
for i=1:n
Z(i)=log((L-Y(i))/Y(i));
end
Zbar= mean(Z);
for i=1:n
z(i)= Z(i)-Zbar;
Tz(i)= Ti(i).*z(i);
end

STz= sum(Tz);
b1 = STz/STi;
lnc= Zbar - (b1.*Tbar);

t=2030;
Zfp = (b1.*t)+lnc;

% ln((L-Y)/Y)= Zfp
% (L-Y)/Y = exp(Zfp)
% L-Y = Y* exp(Zfp)
% L = Y(exp(Zfp)+1)
% Yfp = L/(exp(Zfp)+1)

Yfp = round ( L./(exp(Zfp)+1));


%% -----------------Gompertz--------------------

for i=1:n
Zg(i)=log(-log(Y(i)/L));
end
Zgbar= mean(Zg);

for i=1:n
zg(i)= Zg(i)-Zgbar;
Tzg(i)= Ti(i).*zg(i);
end

STzg= sum(Tzg);
k = STzg/STi;
lnb= Zgbar - (k.*Tbar);
Ztg = lnb+(k.*t);

% ln(-ln(Y/L)= Ztg
% ln(Y/L)= -exp(Ztg)
% Y = L*exp(-exp(Ztg))
Yg =  round (L.*exp(-exp(Ztg)));


%% -------------------- Floyd -------------------------

% Step 1: Compute transform S(Y) = L/(L-Y) + log(Y/(L-Y))
Zf = L./(L - Y) + log(Y./(L - Y));

% Step 2: OLS fit: S = a + b*t
Zfbar = mean(Zf);
```

```
b_floyd = sum((X - Xbar).*(Zf - Zfbar)) / sum((X - Xbar).^2);
a_floyd = Zfbar - b_floyd * Xbar;

% Step 3: Forecast for year t

zf = a_floyd + b_floyd*t;

% Step 4: Closed form inversion with Lambert W
u = lambertw(exp(zf - 1));
Yfloyd = round(L * u / (1 + u));

%% -------------- Plotting --------------------

% (a) Linear Regression Fit
figure;
plot(X, Y, 'ko', 'MarkerFaceColor', 'k', 'DisplayName', 'Actual Data');
hold on;
t_plot = (1983:2030)'; % extended years
Y_lin_plot = a + b * t_plot;
plot(t_plot, Y_lin_plot, 'b-', 'LineWidth', 2, 'DisplayName', 'Linear Fit');
xlabel('Year'); ylabel('RMG Export (in Million USD)');
title('Linear Regression Fit');
legend('Location','NorthWest');
grid on;
ax = gca; ax.YAxis.Exponent = 0; ytickformat('%,.0f');

% (c) Predicted RMG Export in 2030 (Linear)
figure;
plot(X, Y, 'ko', 'MarkerFaceColor', 'k','DisplayName', 'Actual Data');
hold on;
plot(t_plot, Y_lin_plot, 'b-', 'LineWidth', 2);
plot(2030, Ystar, 'rs', 'MarkerFaceColor','r', 'DisplayName','2030
Forecast');
xlabel('Year'); ylabel('RMG Export (in Million USD)');
title('Forecast for 2030 using Linear Regression');
legend('Location','NorthWest');
grid on;
ax = gca; ax.YAxis.Exponent = 0; ytickformat('%,.0f');

% (d) Confidence Interval plot
figure;
plot(X, Y, 'ko', 'MarkerFaceColor', 'k', 'DisplayName', 'Actual Data'); hold
on;
plot(t_plot, Y_lin_plot, 'b-', 'LineWidth', 2, 'DisplayName','Linear Fit');
plot(2030, Ystar, 'rs', 'MarkerFaceColor','r', 'DisplayName','2030
Forecast');
errorbar(2030, Ystar, CI, 'r', 'LineWidth',1.5, 'CapSize',10,
'DisplayName','90% CI');
xlabel('Year'); ylabel('RMG Export (in Million USD)');
title('Forecast with 90% Confidence Interval');
legend('Location','NorthWest');
grid on;
ax = gca; ax.YAxis.Exponent = 0; ytickformat('%,.0f');

% Fisher-Pry
figure;
plot(X, Y, 'ko', 'MarkerFaceColor', 'k', 'DisplayName','Actual Data'); hold
on;
```

```
Z_fp_plot = b1 .* t_plot + lnc;
Y_fp_plot = L ./ (exp(Z_fp_plot) + 1);
plot(t_plot, Y_fp_plot, 'r--', 'LineWidth', 2, 'DisplayName','Fisher-Pry
Fit');
xlabel('Year'); ylabel('RMG Export (in Million USD)');
title('Fisher-Pry Fit');
legend('Location','NorthWest');
grid on;
ax = gca; ax.YAxis.Exponent = 0; ytickformat('%,.0f');

figure;
plot(X, Y, 'ko', 'MarkerFaceColor', 'k', 'DisplayName','Actual Data'); hold
on;
% Gompertz
Z_g_plot = k .* t_plot + lnb;
Y_g_plot = L .* exp(-exp(Z_g_plot));
plot(t_plot, Y_g_plot, 'c-.', 'LineWidth', 2, 'DisplayName','Gompertz Fit');

xlabel('Year'); ylabel('RMG Export (in Million USD)');
title('Gompertz Fit');
legend('Location','NorthWest');
grid on;
ax = gca; ax.YAxis.Exponent = 0; ytickformat('%,.0f');

% Floyd
zf_fit = a_floyd + b_floyd * t_plot;
u_fit = lambertw(exp(zf_fit - 1));
Y_floyd_plot = L * u_fit ./ (1 + u_fit);

% Plot
figure;
plot(X, Y, 'ko', 'MarkerFaceColor', 'k', 'DisplayName','Actual Data'); hold
on;
plot(t_plot, Y_floyd_plot, 'm-', 'LineWidth', 2, 'DisplayName','Floyd Fit');
xlabel('Year'); ylabel('RMG Export (in Million USD)');
title('Floyd Fit');
legend('Location','NorthWest');
grid on;
ax = gca; ax.YAxis.Exponent = 0; ytickformat('%,.0f');
%% --------------- Results --------------------------

fprintf('\n--- Results ---\n');
% (a) Regression Equation
fprintf('(a) Linear Regression Equation: Y=%.2f + %.2f * X\n', a, b);
% (b) R^2 Value
fprintf('(b) Coefficient of Determination (R^2): %.4f\n', R2);
% (c) Forecast for 2030
fprintf('(c) Predicted RMG Export in 2030 (Linear): %.0f\n', Ystar);
% (d) 90%% Confidence Interval
fprintf('(d) 90%% Confidence Interval for 2030 Forecast: [%.0f , %.0f]\n',
Ystar - CI, Ystar + CI);
% (e) Fisher-Pry & Gompertz
fprintf('(e) Predicted Subscribers in 2030:\n');
fprintf('    Fisher-Pry: %.0f\n', Yfp);
fprintf('    Gompertz  : %.0f\n', Yg);
fprintf('    Floyd  : %.0f\n', Yfloyd);
```

b) Weight Smoothing

```
clear all
close all
clc

%% RMG Export of Bangladesh (in Million USD), 1983-2024
X = (1983:2024)';
Y = [ 811;934.43;819.21;1076.61;1231.2;1291.56;1923.7;1717.55;
1993.9;2382.89;2533.9;3472.56;3882.42;4418.28;5161.2;5312.86;
5752.2;6467.3;5986.09;6548.44;7602.99;8654.52;10526.16;
12177.86;14110.8;15565.19;16204.65;22924.38;24301.9;
27027.36;30186.62;31208.94;34257.18;34655.9;
36668.17;40535.04;33674.09;38758.31;
52082.66;46430.71;44469.74;48283.93];

n = numel(Y);
future_years = 2025:2030;
alphas = 0.01:0.01:0.99;    % finer grid of alpha
m = 3;                      % lag window

%% Forecast storage
Forecasts = zeros(numel(future_years), numel(alphas));

%% Loop over each alpha
for a_idx = 1:numel(alphas)
    a = alphas(a_idx);
    Yext = Y;    % extended series for this alpha

    for f = 1:numel(future_years)
        % compute weights for last m lags
        r = (1-a).^(1:m);
        d = (1-a)*(1-(1-a)^m);
        w = a*r/d;

        % take past m years
        past = Yext(end:-1:end-m+1);
        Y_next = sum(w(:).*past(:));

        % save forecast
        Forecasts(f,a_idx) = Y_next;

        % append to extended series
        Yext(end+1) = Y_next;
    end
end

%% Compute min/max range for each year
Forecast_min = min(Forecasts,[],2);
Forecast_max = max(Forecasts,[],2);

%% Plot actual + range envelope
figure; hold on;
fill([future_years fliplr(future_years)], ...
     [Forecast_min' fliplr(Forecast_max')], ...
     [0.9 0.9 1], 'EdgeColor','none', 'DisplayName','Forecast Range
(?=0.01:0.99)');
```

```
plot(X, Y, 'ko-', 'MarkerFaceColor','k', 'DisplayName','Actual Data');
plot(future_years, Forecast_min, 'r--', 'LineWidth', 1.5, 'DisplayName','Min
Forecast');
plot(future_years, Forecast_max, 'g--', 'LineWidth', 1.5, 'DisplayName','Max
Forecast');

%% Highlight 2030 range
min2030 = Forecast_min(end);
max2030 = Forecast_max(end);

plot([2030 2030], [min2030 max2030], 'b-', 'LineWidth', 3,
'DisplayName','2030 Range');
text(2030+0.3, min2030, sprintf('Min = %.0f', min2030), 'Color','r',
'FontWeight','bold');
text(2030+0.3, max2030, sprintf('Max = %.0f', max2030), 'Color','g',
'FontWeight','bold');

xlabel('Year')
ylabel('RMG Export (Million USD)')
title('Forecast Range 2025-2030 (Weighted Smoothing, ?=0.01:0.99)')
legend('Location','NorthWest')
grid on
ax = gca; ax.YAxis.Exponent = 0; ytickformat('%,.0f');
```