



Technology Transfer and Technology Upgrading in Bangladesh's Emerging Electric Vehicle Industry

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Abstract- This study examines the relationship between Technology Transfer (TT) and Technology Upgrading (TU) in the context of Bangladesh's emerging electric vehicle (EV) industry, an early-stage sector in which technology transfer is widely proposed as a channel for building domestic manufacturing capability. Because primary survey data from Bangladeshi EV-sector firms are not yet available, the analysis is conducted on a 300-observation dataset simulated for statistical demonstration purposes, applying the complete quantitative workflow — descriptive statistics, reliability analysis, Pearson correlation, and simple linear regression — that a primary-data study of this relationship would follow. TT and TU are each measured on multi-item five-point Likert scales (four and five items, respectively) and combined into composite scores. Both scales show strong internal consistency (Cronbach's $\alpha = 0.858$ for TT and 0.885 for TU). The composite TT and TU scores are strongly and positively correlated ($r = 0.678$, $p < 0.001$), and a simple linear regression indicates that TT is a significant predictor of TU ($B = 0.659$, $SE = 0.041$, $t = 15.918$, $p < 0.001$), explaining approximately 46.0% of the variance in TU ($R^2 = 0.460$). These results confirm that the analytic pipeline is correctly specified and ready to be applied to real industry data; they are reported as a methodological template rather than as evidence about Bangladesh's actual EV sector. The paper closes with a concrete sampling, instrumentation, and analytic design for the primary-data study that would be required to test the TT–TU relationship among real EV-sector firms. Data-status statement: All quantitative analyses in this manuscript use simulated observations for methodological demonstration. No result is presented as evidence from actual Bangladeshi EV-sector firms.

Keywords- Technology Transfer, Technology Upgrading, Electric Vehicle Industry, Bangladesh, Absorptive Capacity, Survey Research Design, Regression Analysis, Simulated Data.



I. Introduction

The global automobile industry is undergoing a technological transition driven by the rapid development and adoption of electric vehicles (EVs). Unlike internal-combustion vehicles, EVs depend on an integrated set of advanced technologies — batteries, electric motors, power electronics, battery-management systems, charging infrastructure, and digital manufacturing and control systems. For developing economies, the emergence of the EV industry therefore represents more than a transportation shift: it is a potential channel for technological upgrading and industrial capability development.

Domestic firms in emerging markets typically face constraints in advanced production technology, engineering expertise, and R&D capacity. Technology transfer — through foreign direct investment, joint ventures, licensing, supplier relationships, technical cooperation, and training — is commonly proposed as a mechanism for overcoming these constraints [1]. However, the acquisition of foreign technology does not automatically translate into upgraded domestic capability; firms must also possess sufficient absorptive capacity to adapt and improve on what is transferred [9].

Bangladesh's EV ecosystem is at an early stage, with activity emerging in assembly, battery production, component manufacturing, and charging infrastructure, alongside persistent constraints in R&D capacity, technical skills, and domestic supplier depth. Whether technology transfer meaningfully drives technology upgrading in this specific setting is an open empirical question, and one that has not, to the authors' knowledge, been investigated with primary data from Bangladeshi EV-sector firms.

This paper has a deliberately narrow and explicit scope. It uses a 300-observation simulated dataset, built for SPSS-style statistical practice, to work through the full analytic pipeline — descriptive statistics, reliability testing, correlation, and regression — that a primary-data study of Technology Transfer (TT) and Technology Upgrading (TU) in Bangladesh's EV industry would use. All quantitative results reported below describe the simulated dataset only and are intended as (a) a template for the analytic workflow a future study would follow, and (b) groundwork, in the form of an explicit research design in Section IV, for the data collection required to test the relationship



among real firms. The analysis proceeds under a placeholder hypothesis, stated here only to structure the illustrative demonstration:

H1: Within the simulated dataset, Technology Transfer scores are positively associated with Technology Upgrading scores.

II. Literature Review

1. Technology Transfer and Technological Capability

Technology transfer refers to the movement of technological knowledge, production processes, equipment, technical skills, and managerial practices between organizations or countries. In developing economies it is commonly associated with foreign investment, joint ventures, licensing, and technical cooperation [1], [7]. Its developmental value depends on whether it conveys usable knowledge and capability rather than merely physical equipment: domestic firms must understand and be able to adapt what is transferred, which places human capital and organizational learning at the center of effective absorption [9].

2. Technology Upgrading in the EV Industry

Technology upgrading refers to improvements in a firm's technological capabilities, products, processes, equipment, and organizational systems, occurring through advanced machinery, automation, digital manufacturing, and product development [3]. In the EV industry specifically, upgrading spans battery technology, motor and power-electronics systems, battery-management systems, charging technology, vehicle-control software, and digital production systems. For emerging EV industries, the shift from simple assembly toward higher-value manufacturing and engineering activity is the central upgrading challenge.

3. The Technology Transfer–Technology Upgrading Relationship

The conceptual link runs from technology transfer, through absorption, to upgrading and, ultimately, innovation and competitiveness: firms that obtain advanced technology and possess sufficient absorptive capacity are theorized to improve processes, develop new products, and strengthen engineering capability [9], [6]. Comparable logic underlies the broader FDI–growth literature, in which the magnitude of any spillover depends on the host economy's absorptive capacity and financial development [4], [5].



This reasoning motivates the placeholder hypothesis used to structure the illustrative analysis, and it is the relationship the primary-data study proposed in Section IV is designed to test directly in Bangladesh's EV sector.

4. Research Gap and Contribution

Existing work on technology transfer and upgrading in developing-country manufacturing relies mainly on cross-country macro data [7], [8] or on firm-level surveys in other industries and other countries [6]. Neither literature currently offers firm-level evidence on the TT–TU relationship specific to Bangladesh's EV sector. This paper does not fill that gap; it prepares the methodological ground for filling it, by demonstrating the analytic pipeline on simulated data and specifying the primary-data design needed to close the gap properly.

III. Data and Methodology

1. Data Source and Sample Description

The analysis uses the workbook `EV_Management_Strategy_Synthetic_SPSS_300.xlsx`. The workbook's own documentation states explicitly that the 300 rows are synthetic — generated rows for SPSS/SmartPLS practice only, with a fixed random seed for reproducibility — and instructs users not to present the responses as data collected from real Bangladeshi EV firms. This paper follows that instruction throughout: all statistics below describe the simulated sample only. Data screening found no duplicate respondent identifiers and no missing values on any TT or TU item; all TT and TU items take integer values within the intended 1–5 range.

2. Variable Measurement

Table 1: Variable Definition and Measurement

Variable	Code	Items	Scale
Tech. Transfer	TT1–TT4	4	1–5 Likert
Tech. Upgrading	TU1–TU5	5	1–5 Likert

Scale anchors: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree. Composite TT and TU scores were computed as the mean of their respective

items for each simulated respondent. Four analytical steps were carried out, matching the workflow a primary-data study of this relationship would follow: (i) descriptive statistics for the composite scores; (ii) Cronbach's alpha to assess internal consistency; (iii) Pearson correlation between composite TT and TU; and (iv) simple linear regression of TU on TT, $TU = \beta_0 + \beta_1 TT + \epsilon$. All figures were computed directly from the raw item-level data in the workbook.

3. Descriptive Statistics

Table 2: Descriptive Statistics (Composite Scores)

Variable	N	Mean	SD	Min	Max
Tech. Transfer	300	3.488	0.651	1.75	5.00
Tech. Upgrading	300	3.515	0.632	1.60	5.00

Both composite scores sit modestly above the scale midpoint of 3.0, with standard deviations around 0.63–0.65 indicating a moderate, roughly symmetric spread of responses rather than ceiling or floor clustering. Figure 1 presents the mean scores of Technology Transfer and Technology Upgrading; both constructs demonstrate mean values above the midpoint of the five-point Likert scale.

Figure 1. Mean Scores of Technology Transfer and Technology Upgrading

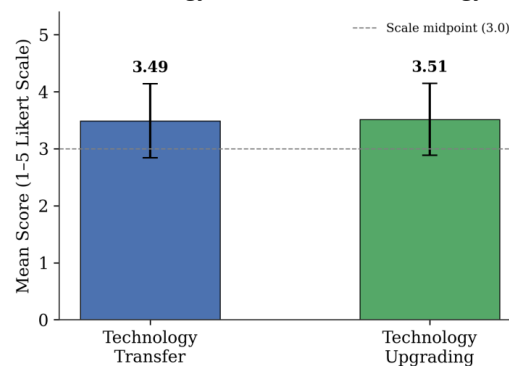


Figure 1. Comparison of the mean scores for Technology Transfer and Technology Upgrading based on the simulated dataset (N = 300).

Figure 2 illustrates the item-level distribution of Technology Transfer, providing a more detailed view of the responses across the four measurement indicators.

Figure 2. Item-Level Mean Scores of Technology Transfer

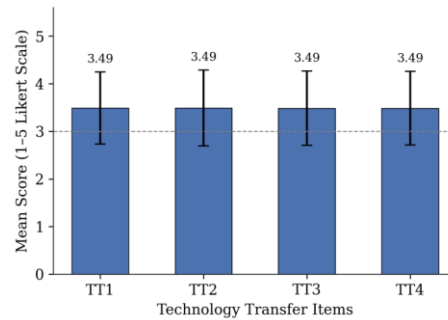


Figure 2. Mean scores of the four measurement items representing Technology Transfer (TT1–TT4).

Figure 3 presents the mean scores for the five Technology Upgrading indicators and provides an overview of the response pattern across the construct.

Figure 3. Item-Level Mean Scores of Technology Upgrading

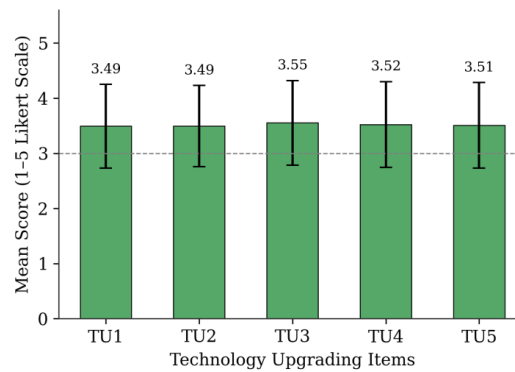


Figure 3. Mean scores of the five measurement items representing Technology Upgrading (TU1–TU5).



4. Reliability Analysis

Table 3: Reliability Analysis

Construct	Items	Cronbach's α
Tech. Transfer	4	0.858
Tech. Upgrading	5	0.885

Both coefficients exceed the conventional 0.70 threshold, indicating that items within each scale co-vary consistently in the simulated data. This is expected: the dataset was generated to produce well-behaved, internally consistent scales for practice purposes, so the high alpha values demonstrate that the simulation succeeded at its intended purpose rather than that any real measurement instrument has been validated.

5. Correlation and Regression Analysis

Table 4: Pearson Correlation Matrix

Variables	Tech. Transfer	Tech. Upgrading
Tech. Transfer	1.000	0.678***
Tech. Upgrading	0.678***	1.000

Note: *** $p < 0.001$ (two-tailed, $N = 300$). The composite TT and TU scores correlate at $r = 0.678$. Within a simulated dataset built around a single generative relationship, a correlation of this magnitude mainly confirms that the intended association was encoded successfully; it is not informative about the true strength of any real-world relationship.

Table 5: Regression Results (DV: Tech. Upgrading)

Predictor	B	SE	t	p
Constant	1.216	0.147	8.282	< 0.001
Tech. Transfer	0.659	0.041	15.918	< 0.001

$R^2 = 0.4595$; Durbin–Watson ≈ 1.90 (no material autocorrelation, as expected for cross-sectional data with arbitrarily ordered rows). The fitted line, $TU = 1.216 + 0.659 \times TT$, implies that within the simulated sample a one-unit increase in composite TT is

associated with a 0.659-unit increase in composite TU, with TT accounting for about 46.0% of the variance in TU. Figure 4 visually demonstrates this positive association; the upward pattern of the observations is consistent with the Pearson correlation coefficient ($r = 0.678$, $p < 0.001$).

Figure 4. Relationship Between Technology Transfer and Technology Upgrading

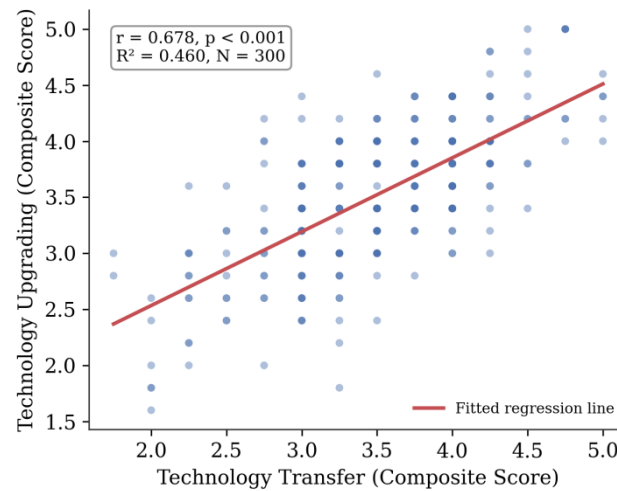


Figure 4. Scatter plot showing the positive relationship between Technology Transfer and Technology Upgrading based on 300 simulated observations ($r = 0.678$, $p < 0.001$).

6. Discussion of Findings

Two things are worth separating clearly. First, as a methodological exercise, the pipeline behaves exactly as intended: reliable-looking scales, a moderate-to-strong correlation, and a regression with a substantial R^2 and no obvious diagnostic problems. This confirms that the workflow described in Section III is well specified and ready to be pointed at real data.

Second, and more importantly, none of these numbers say anything about whether technology transfer actually drives technology upgrading among real EV-sector firms



in Bangladesh. A simulated dataset generated to embody a target relationship will reproduce that relationship by construction; a strong r or R^2 in this context is a check on the simulation, not evidence about the world. The theoretical case that access to external technology, combined with sufficient absorptive capacity, can support upgrading remains a plausible but empirically untested proposition for this specific industry and country context.

It is also worth noting, independent of the synthetic-data issue, that even a well-executed real study using this two-construct design would face real limits: a single-informant, cross-sectional survey with self-reported Likert items is exposed to common-method bias, cannot establish the direction of causality implied by the $TT \rightarrow TU$ path, and — with only two constructs and four/five items each — does not test the fuller antecedent-mediator-outcome model that the broader conceptual framework actually proposes. These are design considerations for the primary-data study outlined in Section IV, not artifacts of using simulated data.

IV. Implications for a Primary-Data Study

1. Target Population and Sampling

Testing the TT – TU relationship in Bangladesh's EV industry requires primary data from actual industry participants: EV manufacturers, assemblers, importers, battery manufacturers, component suppliers, charging-infrastructure providers, and technology partners or joint ventures operating in Bangladesh. Respondents would be drawn through industry associations, BOI/BIDA registries, or trade-body membership lists, given the likely absence of a complete sampling frame for this emerging sector. For a single-predictor regression, conventional power guidance (detecting a medium effect, $f^2 \approx 0.15$, at $\alpha = 0.05$, power = 0.80) suggests a minimum of roughly 55–85 respondents; a target of 150–250 usable responses would provide comfortable power and support a fuller structural model.

2. Instrument Design and Data Collection

A validated or adapted multi-item Likert instrument for TT and TU , drawing on established technology-transfer and absorptive-capacity scales in the literature, should be pre-tested with a small pilot sample. Attention should be paid to translation and



back-translation if the instrument is administered in Bangla, and to using multiple informants per firm where feasible to reduce common-method bias.

3. Extending the Model: Antecedents and Outcomes

The dataset's own documentation situates TT and TU within a broader illustrative model — R&D Investment, Human Capital Development, and Strategic Partnership as antecedents of TT; Innovation Capability and Firm Performance as downstream outcomes of TU; and Government Support as a contextual moderator:

*Strategic Partnership → Technology Transfer → Technology Upgrading →
Innovation Capability → Firm Performance*

Testing this fuller model would require a measurement-model assessment (outer loadings, composite reliability, AVE, discriminant validity/HTMT) and structural estimation such as PLS-SEM with bootstrapped significance testing [10], along with explicit mediation tests for the SP→TT→TU and TU→IC→FP paths.

4. Analytic Plan and Methodological Safeguards

The analytic plan should replicate the descriptive, reliability, correlation, and regression steps demonstrated in Section III, extended with explicit tests for common-method bias (e.g., Harman's single-factor test) and, where the sampling design allows, a longitudinal or at least a two-wave component, since technology upgrading is a multi-year process unlikely to be fully captured cross-sectionally.

Future Research Directions

Several avenues remain for future research. First, once primary data are collected, sectoral disaggregation within the EV industry — separately analyzing assembly operations, component manufacturing, and engineering services — could reveal heterogeneous TT–TU dynamics. Second, firm-level panel data spanning multiple years would allow the direction of causality between TT and TU to be examined more credibly than a cross-sectional design permits. Third, additional institutional variables, such as governance quality, infrastructure development, and R&D expenditure, could be incorporated to reduce omitted-variable bias in the antecedent-outcome model outlined in Section IV.C.



Finally, future work may explore nonlinear relationships or threshold effects between technology transfer and upgrading: it is plausible that TT contributes significantly to TU only after a firm has accumulated sufficient absorptive capacity or reached a minimum level of technical maturity, a possibility that a simple linear model cannot capture.

Future research can extend the two-construct demonstration into the broader model proposed in this study. Strategic Partnership, R&D Investment, and Human Capital Development may be examined as antecedents of Technology Transfer, while Innovation Capability and Firm Performance may be examined as downstream outcomes of Technology Upgrading, with Government Support considered as a contextual moderator. Such a model would require measurement-model assessment and, where justified by the collected data, structural equation modeling with bootstrapping.

Causal identification is another limitation of a cross-sectional TT–TU design. Technology upgrading develops over time, and firms with stronger capabilities may also be more able to obtain external technology. Longitudinal or two-wave data, where feasible, would provide a stronger basis for examining temporal ordering. Additional controls for firm size, firm age, R&D intensity, human capital, government support, and other relevant firm or institutional characteristics could also reduce omitted-variable concerns.

The future study should address common-method bias through procedural as well as statistical safeguards. Where feasible, multiple respondents per firm or temporally separated measurement waves should be used rather than relying exclusively on one respondent and one survey occasion. Harman's single-factor test may be reported as a supplementary diagnostic, but it should not substitute for stronger procedural controls. A future enterprise-level study should collect primary data from firms involved in EV assembly, manufacturing, batteries, components, charging infrastructure, and related technology partnerships. Respondents should preferably include managers with direct knowledge of technology acquisition, production, R&D, training, and upgrading activities. A validated or carefully adapted multi-item questionnaire should be pilot-tested, and Bangla translation should use translation and back-translation procedures where required.



This limitation directly restricts external validity. The reported coefficients cannot be generalized to Bangladesh's actual EV industry, and the study does not establish that technology transfer causes technology upgrading in real firms. Because the simulated dataset was constructed to contain a target relationship, a strong correlation or R^2 is a check on the behavior of the synthetic dataset rather than evidence of the magnitude of a real-world relationship.

The principal limitation of this study is the use of simulated rather than enterprise-collected data. The 300 observations were generated for statistical demonstration and reproducibility; they are not observations from Bangladeshi EV firms. Accordingly, the descriptive statistics, reliability coefficients, correlations, and regression estimates should be interpreted only as demonstrations of the proposed analytical workflow.

Limitations, Validity, and Future Empirical Testing

V. Conclusion

This paper set out to demonstrate, transparently, the quantitative workflow — descriptive statistics, reliability analysis, Pearson correlation, and simple linear regression — that a study of Technology Transfer and Technology Upgrading in Bangladesh's emerging EV industry would use, applying it to a 300-observation dataset explicitly documented as simulated for statistical practice. Within that simulated dataset, TT and TU showed strong internal consistency ($\alpha = 0.858, 0.885$), a strong positive correlation ($r = 0.678, p < 0.001$), and a regression relationship in which TT accounted for roughly 46.0% of the variance in TU ($B = 0.659, p < 0.001$). These results confirm that the analytic pipeline is correctly specified; they do not constitute evidence about Bangladesh's real EV industry and are not presented as such.

The theoretical case for a TT–TU relationship in this setting remains plausible and worth testing, but doing so credibly requires the primary-data study outlined in Section IV — real respondents, a validated instrument, adequate sample size, and attention to common-method bias and causal direction. Until that data collection occurs, any claim about how technology transfer actually affects technology upgrading among Bangladeshi EV firms should be treated as an open question, not a finding.



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