



# WHAT DRIVES BUY NOW, PAY LATER ADOPTION? A DEMATEL-BASED CAUSAL ANALYSIS IN INDIA'S E-COMMERCE SUPPLY CHAIN

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**Abstract:** Buy Now, Pay Later (BNPL) has emerged as an important financial instrument in the rapidly evolving e-commerce landscape of India. It connects advanced digital payment systems with limited access to formal credit. Moreover, the adoption of BNPL is due to both technological advancement and a more profound structural change in the way consumers are using credit in the digital marketplace. Although it is now generally accepted, the underlying drivers and their causal interrelationships remain underexplored, especially in the context of India's rapidly evolving e-commerce supply chain. To address this gap, the study identifies eight key drivers across technology, institutions, and consumer behavioural drivers, conceptually grounded in the Technology Acceptance Model. Furthermore, the eight drivers were validated by experts. To analyse these relationships, the study uses the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method. The results indicate that digital payment infrastructure and regulatory support act as dominant upstream drivers. On the other side, financial inclusion, perceived ease of use and consumer trust are prominent but dependent outcomes, while AI-driven credit assessment functions as a system-dependent capability shaped by upstream conditions. Similarly, strategic partnerships and digital and financial literacy are reinforcing factors. Overall, the findings show that the adoption of BNPL is not just a series of individual choices but rather is hierarchically structured and interconnected. Thus, the study provides practical and policy-relevant recommendations for fintech firms and e-commerce platforms, and policymakers involved in making BNPL adoption inclusive, scalable, and responsible in developing countries.

**Keywords:** Buy Now Pay Later (BNPL), E-commerce supply chain, DEMATEL, Digital payment infrastructure, Technology Acceptance Model, India

## 1. INTRODUCTION/BACKGROUND

Over the past decade, India's e-commerce industry has been experiencing continuous and transformational growth, making it one of the fastest-growing digital markets in the world. The growth is not only rapid but structurally significant. For instance, the market is valued at approximately US\$ 125 billion in 2024 and is expected to grow to over US\$345 billion by 2030 at a compound annual growth rate (CAGR) of around 15% (India Brand Equity Foundation, 2025). The increasing popularity of e-commerce is reshaping India's business landscape as more people opt to shop online. As more consumers opt to purchase online rather than in-store, the demand for payment solutions has become more important than ever before. Within this context, Buy Now, Pay Later (BNPL) has emerged as an innovative financial instrument that allows consumers to purchase goods and services immediately, while making payment later on by paying in instalments (Mukherjee, 2025). The global BNPL market was valued at approximately USD 44.89 billion as of 2025 and most likely to reach USD 286.02 billion by 2034, growing at a CAGR rate of 23% during the forecast period (Fortune Business Insights, 2026). Globally, the number of BNPL users is estimated to hit 380 million in the year 2024 and further reach to 670 million by 2028 (Juniper Research, 2024). As per these trends, the role of BNPL is certainly not going to be just a substitute for other payment methods. BNPL seems to be a structurally important mechanism reshaping consumption behaviour in digital commerce.

Furthermore, the evidence shows it affects consumer credit behaviour. Most significantly, BNPL users increase their monthly spending by approximately 11.2%, which suggests a rise in consumption intensity (Maeng et al., 2023). BNPL services are gaining popularity for offering features such as instant approval, flexible repayment options, paperless processes, and interest-free credit (Behera et al., 2024). The intention of consumers to adopt BNPL can be significantly influenced by performance expectancy, effort expectancy, social influence, and habit (Raj et al., 2025). The influence of such behaviour among consumers reinforces BNPL's position as a key enabler of e-commerce.

From an e-commerce perspective, BNPL improves transaction outcomes by increasing conversion rates and raising cart values, and decreasing cart abandonment, while also strengthening customers' purchasing power (Lupşa-Tătaru et al., 2023). Consumers are likely to spend more when the price is separated over two or more payments, as this feels easier to manage (Maesen & Ang, 2025; Waliszewski et al., 2025). BNPL changes the conventional transaction structures. The merchant receives full payment for the goods or services at the point of sale (POS) since the credit risk is shifted to the BNPL providers. This effectively separates financing from retail transactions. BNPL providers act as intermediaries within the platform ecosystems in which BNPL providers derive value from commissions paid by merchants, and leveraging existing infrastructure (Tan, 2022). So, BNPL adds an embedded layer of financing that is incorporated into the platforms in order to facilitate better transactions and demand realisation within the e-commerce supply chain.

In contrast to global trends, a structural paradox exists in the Indian context. Even as the digital payments have grown rapidly and occupy a dominant share of total payments (97.6 per cent) in 2024-25, access to formal credit remains limited (Reserve Bank of India, 2025). About 90% of adults have financial accounts, but a large segment remains excluded from the formal borrowing systems (Klapper et al., 2025). This creates a gap between payment accessibility and the availability of credit. While individuals may be digitally connected, these people are not getting the necessary credit. In addition, the use of digital payment systems is significantly higher than formal borrowing, suggesting a clear gap between payment usage and credit access (Klapper et al., 2025). It raises key questions about the role of BNPL in India's financial ecosystem.

The BNPL system involves the consumers, the merchants, the fintech firms, the NBFCs, and the regulatory institutions. The effectiveness of the process is dependent on interactions between these actors, where value creation is distributed rather than centralised. This system comes with regulatory frameworks that allow innovation while ensuring compliance in the digital lending environment. E-commerce platforms are becoming more embedded with BNPL players. For instance, Flipkart, Myntra and Amazon have BNPL integrations on their checkout page (S. Kumar & Nayak, 2025). Consequently, BNPL adoption cannot be explained in terms of individual-level factors alone. It must be seen as a function of the interaction between individuals, payment service providers, and merchants.

At the consumer level, there are a variety of interlinked factors that influence BNPL adoption. The Technology Acceptance Model is a useful theoretical lens as it identifies the perceived ease of use and perceived usefulness that influence technology adoption (Davis, 1989). In the context of BNPL, these factors are reflected in platform usability, transaction speed, and perceived financial flexibility. However, adoption outcomes are not the same among users, where digital and financial literacy affect users' ability to access and use them effectively (Juita et al., 2024). In India, particularly in rural areas, low literacy levels act as another barrier to adoption (Mukherjee, 2025). Another study conducted on Indian BNPL users demonstrated that privacy risk and financial risk have reduced customers' behavioural intention to adopt BNPL services (Raj et al., 2025). Accordingly, such factors indicate that BNPL adoption is shaped by an interaction of technological, behavioural, and contextual influences.

Despite the growing complexity, the existing literature on BNPL has several key limitations. Much of the BNPL research is concentrated in developed markets like Australia, the United Kingdom, and other advanced economies, revealing an obvious population gap in the literature (Mukherjee, 2025). Recent studies mostly focus on consumer behaviour, over-indebtedness, and regulatory concerns (S. Kumar & Nayak, 2025). As a result, the findings are less applicable in the Indian context due to low formal credit penetration, evolving regulatory frameworks, and persistent gaps in digital literacy. Beyond contextual limitations, most studies rely on linear adoption models that define BNPL uptake primarily as a function of individual attitudes and perceptions. While such approaches may be useful, they do not account for how BNPL adoption is a dynamic interaction of technology, institution and behaviour.

Moreover, existing research has largely concentrated on barriers, such as over-indebtedness and regulatory concerns, which largely offer a constraint-oriented view. Although Mukherjee (2025) provides a foundational contribution through the application of the DEMATEL approach to examine barriers in the Indian context, the enabling drivers facilitating BNPL adoption remain unaddressed. It is equally important because previous studies do not adequately conceptualise BNPL adoption as interrelated drivers operating within a supply chain framework. Accordingly, the causal relations of these drivers and their relative influence remain insufficiently understood. To address these gaps, the present study identifies eight key enabling drivers of BNPL adoption in India's e-commerce supply chain and examines their causal interrelationships using the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method. Due to the interdependencies of various factors, DEMATEL is appropriate for mapping the direct and indirect relationships between the drivers. Consequently, it helps to understand the structural dynamics underlying BNPL adoption. The adoption process is multi-layered, and these drivers can be technological, institutional, and consumer-behavioural. Accordingly, the research study is guided by these questions:

RQ1. What are the critical drivers enabling BNPL adoption in India's e-commerce supply chain?

RQ2. What causal relationships exist among these drivers, and which function as the primary upstream driver?

Using this framework, the study makes four important contributions. Firstly, it situates the adoption of BNPL in a wider system of interdependent drivers, extending the application of the Technology Acceptance Model beyond just individual-level explanations (Davis, 1989). In addition, it shifts the focus from barriers to enabling mechanisms, thereby offering a more balanced perspective on BNPL adoption in India. Using DEMATEL, the study reveals the causal structure among drivers and their relative influence in the hierarchy of the system. Finally, these findings provide actionable insights for fintech firms, e-commerce platforms, and policymakers by identifying important leverage points for promoting inclusive and responsible BNPL adoption. The rest of the paper is organised as follows: Section 2 identifies and defines the eight enabling drivers through a literature review, expert validation, and Section 3 discusses the research methodology. Section 4 shows the results, followed by a discussion of findings in Section 5. Finally, Section 6 concludes the study while discussing the limitations and directions for future study.

## 2. IDENTIFICATION AND VALIDATION OF ENABLING DRIVERS

In order to examine the adoption of BNPL within India's e-commerce supply chain, it is important to identify the key enabling drivers. Instead of treating these factors in isolation, this study adopts an integrated view recognising that adoption is a function of technological, institutional, and consumer-behavioural dimensions. This integrated approach is particularly relevant in platform-based ecosystems, where adoption outcomes are influenced by interdependencies across multiple actors and processes.

Following the review of previous studies on digital credit, BNPL adoption, and financial inclusion, an initial set of fourteen drivers was identified. The Technology Acceptance Model provides a foundational framework, highlighting perceived ease of use and

perceived usefulness as the main determinants of adoption (Davis, 1989). However, given the embedded nature of BNPL within e-commerce platforms, TAM is insufficient to capture system-level influences. Consequently, additional drivers related to digital infrastructure, regulatory support, and ecosystem coordination were added to capture the broader context of the supply chain. The drivers that are identified were further validated by the experts to ensure contextual relevance and practical validity. A panel of five domain experts from both the industry and academia analysed the relevance and importance of all drivers. Therefore, it integrates the expertise of domain experts and minimises any chance of theoretical bias. As a result of this evaluation, the initial set of fourteen drivers was refined to eight key enabling drivers through a consensus-based approach. This refinement process resulted in final drivers that are both analytically meaningful and empirically relevant within the Indian BNPL ecosystem. As shown in Table 1, the final set of drivers relates to infrastructure, regulatory, and consumer factors that capture the multi-dimensional nature of BNPL adoption.

**Table 1.** Enabling Drivers of BNPL Adoption

| Code | Driver                                                                   | Description                                                                                                                                                                                                                                                                                                                                                               | References                                                |
|------|--------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------|
| D1   | Perceived ease of use reflecting effort expectancy in BNPL services      | The extent to which consumers find the BNPL services easy to use, intuitive, and require minimal effort. Through streamlined procedures and effortless transactions, friction is minimised, and convenience is enhanced.                                                                                                                                                  | Davis (1989); A. Kumar et al. (2024); Raj et al. (2025)   |
| D2   | Availability of digital payment infrastructure enabling BNPL integration | The efficiency of BNPL depends on the digital payment infrastructure. For instance, the use of UPI in India, along with accessibility to smartphones and internet access, allows for real-time transactions and platform integration. It enables scaling of BNPL operations efficiently and effectively.                                                                  | Maeng et al. (2023); Klapper et al. (2025)                |
| D3   | Regulatory framework and policy support for BNPL expansion               | At the institutional level, regulatory support assists the development and continuity of BNPL services. Digital lending with clear policies and guidelines can foster responsible innovation. Such frameworks promote trust and foster sustainable ecosystem development.                                                                                                 | Behera et al. (2024); S. Kumar & Nayak (2025)             |
| D4   | Consumer trust and data privacy assurance in BNPL platforms              | User trust in data management and platform transparency affects the adoption of BNPL services. As these platforms require personal and financial information, improved privacy safeguards and regulatory protections help in reducing the perceived risk.                                                                                                                 | Mukherjee (2025); Raj et al. (2024); Tan (2022)           |
| D5   | Financial inclusion and credit accessibility for underserved segments    | BNPL provides a mechanism for financial access in situations where formal credit access is limited. It allows unprivileged customers to avail short-term credits and transact online more actively by skipping the formal credit requirements.                                                                                                                            | A. Kumar et al. (2024); Maeng et al. (2023)               |
| D6   | Strategic partnership between BNPL providers, merchants, and NBFCs       | Partnerships are necessary at the ecosystem level for seamless BNPL delivery. The partnerships of BNPL providers with e-commerce platforms and NBFCs help in sharing risk, platform integration, and scaling of digital commerce.                                                                                                                                         | Behera et al. (2024); S. Kumar & Nayak (2025); Tan (2022) |
| D7   | AI-driven credit assessment and risk management in BNPL                  | AI allows for instant and data-oriented credit decisions. BNPL providers evaluate users with limited or no credit history using alternative data points such as transaction history and digital footprints. This strategy significantly improves risk management and inclusion.                                                                                           | Behera et al. (2024); Tan (2022)                          |
| D8   | Digital and financial literacy among BNPL users                          | The level of consumers' digital and financial literacy will determine their usage of BNPL services. Those with higher literacy levels take informed decisions, use instruments responsibly and understand repayment obligations better. On the contrary, when someone has low literacy, they can have limited access and increase the likelihood of misuse or exclusions. | Ainy et al. (2025); Juita et al. (2024)                   |

### 3. RESEARCH METHODOLOGY

#### 3.1 Research Design

The present study adopts an exploratory causal research design grounded in the Multi-Criteria Decision-Making (MCDM) approach. This design is suitable for assessing complex systems with multiple interdependent variables, which may not be effectively captured by linear methods. In the context of BNPL adoption, these drivers are not isolated but interrelated in a broader system. Due to this complexity, the expert-based evaluation becomes essential for capturing both practical relevance and theoretical rigour (Mukherjee, 2025). Accordingly, a purposive panel of five experts (as shown in Table 2), comprising three industry practitioners and two academic researchers were selected. Through a wide range of knowledge streams, the experts conveyed operational know-how and theoretical knowledge about the credit risk of financial products, banking and digital lending, the financial system, and supply chain research. Collectively, the panel's domain experience between 8 and 13 years ensured informed and balanced judgment. To minimise bias, each expert independently evaluated the relationships among the identified drivers. The pairwise influence

assessments were captured in a structured questionnaire to ensure consistency. This approach ensured that the data reflected both real-world and conceptual experience.

**Table 2.** Expert Panel Profile

| Expert | Position               | Years of Experience |
|--------|------------------------|---------------------|
| E1     | Credit Risk Manager    | 8                   |
| E2     | Zonal Manager          | 10                  |
| E3     | Senior Product Manager | 13                  |
| E4     | Associate Professor    | 12                  |
| E5     | Assistant Professor    | 9                   |

### 3.2 DEMATEL Procedure

DEMATEL, which was developed at the Geneva Research Centre of the Battelle Memorial Institute (Gabus & Fontela, 1972), is a systematic approach for modelling the causal relations in complex systems. DEMATEL has been widely recognised as an effective method for analysing enabling factors and their causal interrelationships within supply chain systems, thereby supporting its methodological suitability for the present study (Tyagi et al., 2015). The study's procedural steps for DEMATEL applications are adopted from Mukherjee (2025) and Srivastava et al. (2026) and are as follows:

#### Step 1: Pairwise Assessment & Construction of the Average Direct-Relation Matrix (ADRM)

Each expert uses a predefined linguistic scale (Table 3), to evaluate the direct influence of driver  $i$  on driver  $j$ . These individual judgements will be aggregated into the ADRM, denoted as matrix  $Z$ ,

$$Z = \frac{1}{H} \sum_{k=1}^H x_{ij}^k$$

where  $H$  denotes the number of experts and  $x_{ij}^k$  represents the score assigned by the expert  $k$ .

**Table 3.** Linguistic Scale for Expert Judgments

| Score | Linguistic Term     |
|-------|---------------------|
| 0     | No Influence        |
| 1     | Low Influence       |
| 2     | Medium Influence    |
| 3     | High Influence      |
| 4     | Very High Influence |

#### Step 2: Construction of the Normalised Direct-Relation Matrix (NDRM)

The direct-relation matrix is normalised to ensure comparability. Each element of matrix  $Z$  is normalised by a scalar value derived from the maximum row or column sum. Normalisation ensures that all elements of matrix  $D$  will be in the range  $[0, 1]$ .

$$D = \frac{Z}{s}$$

$$s = \max \left( \max_{1 \leq i \leq n} \sum_{j=1}^n z_{ij}, \max_{1 \leq j \leq n} \sum_{i=1}^n z_{ij} \right)$$

#### Step 3: Construction of the Total Relation Matrix (TRM)

The TRM is calculated from the normalised matrix to understand the direct and indirect relationships among the drivers. It is computed as:

$$T = D(I - D)^{-1}$$

where  $I$  denote the identity matrix.

#### Step 4: Calculation of Prominence and Relation Values

For each driver, the TRM generates two key indicators. The row sum  $r_i$  indicates the total influence that driver  $i$  exerts, and the column sum  $c_j$  indicates the total influence driver  $j$  receives.

$$r_i = \sum_{j=1}^n t_{ij}$$

$$c_j = \sum_{i=1}^n t_{ij}$$

The prominence value  $(r_i + c_j)$  shows the overall importance of a driver in the system. In contrast, the relation value  $(r_i - c_j)$  determines whether a driver belongs to the cause group (positive value) or the effect group (negative value).

### Step 5: Construction of the Causal Diagram

In the end, a causal diagram is created to illustrate the relationships between drivers. The average value of all the TRM elements is a threshold value, and only significant relationships that exceed this value are retained. Each driver is then plotted with prominence along the x-axis and relation along the y- axis. This representation clearly distinguishes causal drivers and reveals the hierarchy of BNPL adoption drivers.

## 4. RESULTS AND ANALYSIS

### 4.1 Average Direct-Relation Matrix (Z)

Table 4 presents the Average Direct-Relation Matrix (Z), which was constructed by aggregating the pairwise influence scores provided by the expert panel. The results indicate that influence is unevenly distributed across the system. Notably, digital payment infrastructure (D2) has the highest row sum, which indicates a strong outward influence. On the other hand, the influence of drivers such as AI-driven credit assessment (D7) is relatively less. The matrix shows the presence of hierarchical relationships among drivers.

**Table 4.** Average Direct-Relation Matrix (Z)

| i/j        | D1     | D2     | D3     | D4     | D5     | D6     | D7     | D8     | row sum |
|------------|--------|--------|--------|--------|--------|--------|--------|--------|---------|
| D1         | 0.000  | 2.600  | 1.800  | 3.200  | 3.800  | 2.000  | 2.600  | 3.200  | 19.200  |
| D2         | 3.200  | 0.000  | 2.800  | 2.000  | 3.000  | 3.200  | 3.600  | 2.000  | 19.800  |
| D3         | 2.200  | 2.400  | 0.000  | 3.200  | 2.800  | 3.200  | 2.000  | 1.600  | 17.400  |
| D4         | 2.600  | 2.000  | 2.400  | 0.000  | 3.200  | 2.000  | 3.000  | 2.800  | 18.000  |
| D5         | 3.400  | 2.000  | 2.000  | 2.600  | 0.000  | 3.000  | 2.000  | 3.200  | 18.200  |
| D6         | 2.600  | 3.200  | 2.200  | 2.000  | 3.200  | 0.000  | 3.000  | 2.000  | 18.200  |
| D7         | 2.200  | 3.000  | 1.000  | 3.000  | 3.200  | 2.400  | 0.000  | 2.000  | 16.800  |
| D8         | 3.000  | 2.000  | 1.800  | 3.000  | 4.000  | 2.000  | 2.200  | 0.000  | 18.000  |
| column sum | 19.200 | 17.200 | 14.000 | 19.000 | 23.200 | 17.800 | 18.400 | 16.800 |         |

### 4.2 Normalised Direct-Relation Matrix (D)

As shown in Table 5, the ADRM was normalised so that all values would lie in a comparable range [0, 1]. From this perspective, the influence levels of drivers, specifically digital payment infrastructure (D2) and financial inclusion (D5), are relatively high. This strengthens the interconnectedness of BNPL adoption.

**Table 5.** Normalised Direct-Relation Matrix (D)

| Drivers | D1    | D2    | D3    | D4    | D5    | D6    | D7    | D8    |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|
| D1      | 0.000 | 0.112 | 0.078 | 0.138 | 0.164 | 0.086 | 0.112 | 0.138 |
| D2      | 0.138 | 0.000 | 0.121 | 0.086 | 0.129 | 0.138 | 0.155 | 0.086 |
| D3      | 0.095 | 0.103 | 0.000 | 0.138 | 0.121 | 0.138 | 0.086 | 0.069 |
| D4      | 0.112 | 0.086 | 0.103 | 0.000 | 0.138 | 0.086 | 0.129 | 0.121 |
| D5      | 0.147 | 0.086 | 0.086 | 0.112 | 0.000 | 0.129 | 0.086 | 0.138 |
| D6      | 0.112 | 0.138 | 0.095 | 0.086 | 0.138 | 0.000 | 0.129 | 0.086 |
| D7      | 0.095 | 0.129 | 0.043 | 0.129 | 0.138 | 0.103 | 0.000 | 0.086 |
| D8      | 0.129 | 0.086 | 0.078 | 0.129 | 0.172 | 0.086 | 0.095 | 0.000 |

### 4.3 Total Relation Matrix (T)

As shown in Table 6, the TRM captures the direct and indirect influence of the drivers. An analysis of row sums  $r_i$  indicates that D2 has the strongest overall influence. Conversely, column sums  $c_j$  suggest that financial inclusion (D5) is the most influenced driver. Together, these results distinguish between driving and dependent factors within the system.

**Table 6.** Total Relation Matrix (T)

| Drivers | D1    | D2    | D3    | D4    | D5    | D6    | D7    | D8    | $r_i$ |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| D1      | 0.411 | 0.464 | 0.376 | 0.522 | 0.624 | 0.456 | 0.489 | 0.491 | 3.833 |
| D2      | 0.540 | 0.377 | 0.418 | 0.491 | 0.607 | 0.510 | 0.535 | 0.455 | 3.934 |
| D3      | 0.461 | 0.429 | 0.279 | 0.487 | 0.546 | 0.468 | 0.437 | 0.401 | 3.507 |
| D4      | 0.485 | 0.423 | 0.378 | 0.378 | 0.574 | 0.434 | 0.479 | 0.454 | 3.604 |
| D5      | 0.519 | 0.428 | 0.369 | 0.483 | 0.461 | 0.473 | 0.451 | 0.473 | 3.657 |
| D6      | 0.492 | 0.471 | 0.376 | 0.461 | 0.579 | 0.361 | 0.487 | 0.429 | 3.657 |
| D7      | 0.452 | 0.440 | 0.314 | 0.469 | 0.549 | 0.429 | 0.348 | 0.407 | 3.408 |

|           |       |       |       |       |       |       |       |       |       |
|-----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| <b>D8</b> | 0.502 | 0.423 | 0.359 | 0.493 | 0.603 | 0.435 | 0.453 | 0.350 | 3.618 |
| $c_j$     | 3.862 | 3.455 | 2.868 | 3.785 | 4.543 | 3.565 | 3.680 | 3.461 |       |

#### 4.4 Prominence and relation values

The prominence and relation values derived from the TRM are presented in Table 7. The prominence value ( $r_i + c_j$ ) indicates the importance of the drivers in the system. The relation value ( $r_i - c_j$ ) determines whether a driver is part of the cause or effect group. The analysis shows that financial inclusion (D5), ease of use (D1), and consumer trust (D4) are the prominent drivers. However, the negative values classify them as dependent outcomes. Conversely, digital payment infrastructure (D2), regulatory framework (D3), strategic partnerships (D6), and digital literacy (D8) are causal drivers. This indicates that structural drivers shape key outcomes.

**Table 7.** Prominence and Relation Values

| Driver (code) | $r_i$  | $c_j$  | $(r_i + c_j)$ | $(r_i - c_j)$ | Rank | Identity |
|---------------|--------|--------|---------------|---------------|------|----------|
| <b>D5</b>     | 3.6573 | 4.5435 | 8.2008        | -0.8861       | 1    | Effect   |
| <b>D1</b>     | 3.8330 | 3.8621 | 7.6951        | -0.0291       | 2    | Effect   |
| <b>D4</b>     | 3.6044 | 3.7849 | 7.3894        | -0.1805       | 3    | Effect   |
| <b>D2</b>     | 3.9342 | 3.4548 | 7.3890        | 0.4794        | 4    | Cause    |
| <b>D6</b>     | 3.6570 | 3.5651 | 7.2221        | 0.0919        | 5    | Cause    |
| <b>D7</b>     | 3.4082 | 3.6796 | 7.0878        | -0.2713       | 6    | Effect   |
| <b>D8</b>     | 3.6179 | 3.4605 | 7.0784        | 0.1573        | 7    | Cause    |
| <b>D3</b>     | 3.5068 | 2.8684 | 6.3752        | 0.6383        | 8    | Cause    |

#### 4.5 Causal diagram

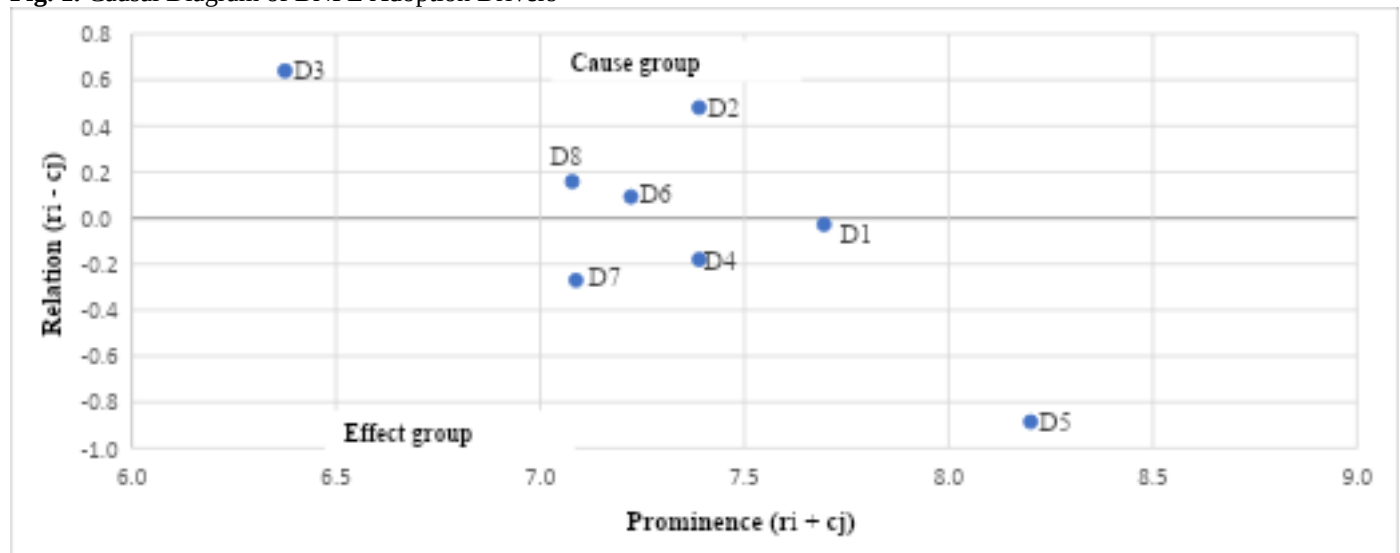
To visualise these relationships, a causal diagram was developed based on prominence and relation values (as shown in Figure 1). The upper half drivers of the cause group include digital payment infrastructure (D2), regulatory framework (D3), strategic partnerships (D6), and digital literacy (D8). Among these, the regulatory framework (D3) is the most influential factor. On the other hand, the effect group includes drivers like financial inclusion (D5), ease of use (D1), consumer trust (D4), and AI-driven credit assessment (D7). Notably, financial inclusion seems to be the most prominent yet highly influenced driver. Overall, the diagram shows a clear structure, where infrastructure and regulatory factors drive the system, and consumer-level outcomes are dependent variables.

### 5. DISCUSSION

This study answers both the research questions by identifying the enabling drivers (RQ1) and the causal structure of their interactions (RQ2) in the BNPL-enabled e-commerce supply chain in India. The overall findings suggest that the adoption of BNPL (Buy Now, Pay Later) is not due to isolated factors, but a structured and interdependent system.

In relation to RQ1, the findings suggest that BNPL adoption is determined by technological, institutional, and consumer-related factors. Financial inclusion and credit accessibility (D5) is the most prominent driver. This shows that BNPL is being used as a last-mile credit in a context of low credit penetration. Notably, financial inclusion is an outcome of underlying system conditions rather than an independent causal force. In other words, financial inclusion is endogenously determined by the BNPL ecosystem. The study is consistent with earlier studies, which show that BNPL largely benefits underserved and credit-invisible segments (A. Kumar et al., 2024; Maeng et al., 2023). Moreover, ease of use (D1) and consumer trust (D4) are also very prominent. These results revealed that the user-friendly and simple procedures that improve perceived ease are essential for user engagement.

However, addressing RQ2 reveals a more nuanced interpretation. Although financial inclusion, perceived ease of use, and consumer trust appear prominent, their negative relation values indicate that they function primarily as outcome variables within the system. In contrast, digital payment infrastructure (D2) and regulatory framework (D3) emerge as dominant upstream drivers having a substantial causal influence. This suggests that the adoption of BNPL fundamentally relies on the maturity of the digital payment infrastructure and the coherent regulatory support. From a supply chain perspective, these upstream drivers help coordinate platform actors, thus ensuring transaction efficiency and credit delivery mechanisms. A similar pattern is consistent with earlier studies that highlight the role of infrastructure readiness and institutional frameworks as key enablers of BNPL adoption (Lupşa-Tătaru et al., 2023). Simultaneously, the key role of regulation highlights the growing importance of policy in shaping trust, compliance, and scalability of fintech-driven models. The findings further indicate that strategic partnerships (D6) and digital and financial literacy (D8) play reinforcing roles within the system. Rather than acting as primary drivers, these factors operate as linkages that strengthen the transmission of effects across the system. Strategic partnerships facilitate integration, risk-sharing, and scalability across platforms, while literacy determines the extent to which users can access and use BNPL services. In the Indian context, studies reveal that social influence plays a significant role in behavioural intention (Raj et al., 2025). Taken together, these factors reinforce the view that BNPL adoption is mediated by both ecosystem coordination and user capability, bridging structural enablers and behavioural outcomes. Additionally, AI-driven credit assessment (D7), although classified within the effect group, plays an important operational role in the BNPL ecosystem. Its position as a dependent factor indicates that the effectiveness of AI-based credit evaluation is contingent upon upstream infrastructural and institutional conditions. In particular, access to reliable digital transaction data, supported by robust payment infrastructure, along with clear regulatory frameworks, enhances the accuracy and scalability of alternative credit assessment mechanisms. This suggests that AI-driven credit assessment functions as a system-dependent capability shaped by upstream infrastructural and regulatory conditions, rather than operating as an independent driver of adoption. This finding aligns with the broader supply chain literature, which suggests that the benefits of AI-enabled digital strategies are realized only when supported by a mature and coherently integrated digital infrastructure (Sharma et al., 2026).

**Fig. 1.** Causal Diagram of BNPL Adoption Drivers

The research contributes to the existing literature and addresses the gaps in multiple ways. Firstly, it defines the BNPL adoption as a hierarchical framework where the upstream drivers influence the downstream outcomes like trust, accessibility, and inclusion. Furthermore, it moves beyond linear adoption models and explicitly models causal interdependencies among drivers. Notably, results extended the Technology Acceptance Model, highlighting that user-centric constructs like perceived ease of use and trust are driven by upstream structural conditions. Ultimately, the study provides a more balanced perspective on BNPL diffusion in emerging markets by emphasising the enabling mechanisms instead of barriers.

Moreover, results indicate that enhancements in consumer-facing outcomes cannot be achieved in isolation. An effective implementation of BNPL requires the strengthening of the foundational drivers like digital infrastructure, regulatory clarity, and coordination among the ecosystem. As a result of these structural drivers, there is a downstream impact on trust, usability, and financial inclusion. This suggests that BNPL is more than a payment innovation. Indeed, BNPL is embedded within a broader digital-institutional ecosystem.

The study presents several important implications. Fintech companies and BNPL providers should focus on improving platform integration and building partnerships with e-commerce platforms and NBFCs for scalability and risk-sharing. To enhance perceived ease of use and transaction convenience, e-commerce platforms can embed seamless BNPL options into user interfaces. At the policy level, the importance of digital infrastructure and regulatory clarity highlights the demand for sustained investment in public digital systems and adaptive regulatory frameworks for digital credit. Moreover, enhancing digital and financial literacy will be crucial in enabling responsible and inclusive adoption, especially for underserved segments. Collectively, these implications emphasise that effective BNPL requires coordinated efforts across technological, institutional, and user-level dimensions.

## 6. CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

This study examines the enabling drivers of BNPL adoption in India's e-commerce supply chain and examines their causal interrelationships using the DEMATEL method. The findings demonstrate that BNPL adoption is not driven by isolated determinants but rather emerges from a structured and interconnected system of drivers operating across technological, institutional, and behavioural dimensions. Financial inclusion, perceived ease of use, and consumer trust are the most prominent drivers. However, they primarily function as outcomes influenced by deeper structural conditions. On the other hand, digital payment infrastructure, regulatory framework, policy support, strategic partnerships, and digital and financial literacy act as key causal drivers affecting the adoption ecosystem. This highlights that BNPL adoption is fundamentally an ecosystem-level phenomenon, where upstream infrastructural and policy conditions shape downstream consumer behaviour.

Despite these contributions, the study has certain limitations. The findings are based on a small expert panel, which may reduce the diversity and generalisability of the findings. The expert-based evaluation, though appropriate for exploratory causal modelling, could be made more robust in future studies through the addition of multiple stakeholders, especially policymakers, fintech practitioners and end-users. Furthermore, the study's cross-sectional nature does not capture the evolution of BNPL adoption over time. Longitudinal approaches would most probably capture temporal changes in causal relationships as the digital lending ecosystem continues to evolve. Third, the focus on the Indian context may constrain the applicability of the findings to other institutional environments with different levels of digital infrastructure and regulatory maturity. While analytically insightful, this context-specific focus limits the external validity of the findings across different markets.

Future studies could adopt comparative cross-country analyses to examine how variations in institutional frameworks influence BNPL adoption dynamics. Additionally, integrating DEMATEL with complementary methods such as Structural Equation Modelling (SEM) or other MCDM approaches could help validate and generalise the causal relationships identified in this study. Further research may also explore user-level behavioural data to better understand how system-level drivers translate into actual adoption patterns and financial outcomes. Collectively, these avenues would contribute to a more comprehensive, dynamic, and empirically grounded understanding of BNPL adoption across diverse economic contexts.

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