CAMELOT Management Consultants

Monetizing Data: A Qualitative Study on Pricing Mechanisms in Data Marketplaces

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As data products become increasingly valuable in data marketplaces, understanding the pricing mechanisms that attract actors to these platforms is of paramount importance. This study presents a comprehensive literature review focused on pricing mechanisms for data products. The analysis reveals a diverse range of pricing approaches, including single request pricing, auction mechanisms, theoretical and conceptual models, package pricing, subscription-based models, and two-part tariffs. By synthesizing the existing research, this study provides insights into the various pricing strategies employed in data marketplaces. The findings contribute to the understanding of pricing dynamics in data product monetization and offer guidance for data marketplace operators and actors in developing and deploying effective pricing strategies. Further research directions are identified to explore the evolving landscape of pricing mechanisms in data marketplaces.

1. Pricing – A challenge in data products and marketplaces

The digital age, dominated by artificial intelligence, machine learning, and Internet of Things (IoT), has made data a critical asset for businesses. Data are valuable for various purposes, from descriptive reasoning, diagnostic understanding, prediction of future events to prescriptive directives and action recommendations. Whatever method is used to analyze data, the goal is to support and drive data informed business decisions. While some enterprises have the necessary access to data internally, others rely on marketplaces for their data needs. Yet, accurately pricing this data is a major challenge that these marketplaces face (Cong et al., 2022; Liang et al., 2018; Y. Shen et al., 2022).

Despite increasing demand for data, many marketplaces have struggled to sustain themselves and have eventually disappeared (Cosgrove & Kuo, 2020). One significant issue that contributes to this failure is the limited commercial usage of these platforms, leading to insufficient profitability (Bergman et al., 2022). For data providers, maximizing profits is generally the goal, thus pricing becomes an essential factor in successful data monetization. Unsuitable prices for data products discourage potential buyers, resulting in missed revenue opportunities (Fricker & Maksimov, 2017). Hence, providers must strike a balance with pricing, ensuring it is attractive to buyers yet profitable.

Given the unique properties of data products, traditional pricing mechanisms, such as cost-plus pricing, fall short in their effectiveness (Pei, 2020). The value of these products is also highly dependent on the individual use case, adding to the complexity of pricing data products. This context sets the foundation for exploring what pricing mechanisms have been discussed in scientific literature that can effectively attract actors to data marketplaces.

2. Leading research question for this study

As the value of data increases, the establishment of suitable pricing mechanisms for data products becomes a central concern. Despite its significance, existing research on this subject appears fragmented and lacks consensus. This study aims to provide a unified overview of the various pricing approaches for data products in scientific literature. The Research Question (RQ) that guides this study is:

What pricing mechanisms are discussed in the scientific literature for data products to attract actors in data marketplaces?

Given the unique properties of data, such as its virtually negligible replication costs, it stands apart from tangible products. This uniqueness necessitates a departure from traditional cost-based pricing approaches, leading to the consideration of distinct mechanisms. This exploration forms the basis of our research question.

3. Definition of important terminology

When it comes to data products and data marketplaces, there is a variety of different understandings. To avoid confusion, important terms are now defined as they are understood in this work. First, the term data product is defined and delimited, followed by a definition of data marketplaces in the sense of this work.

3.1. DEFINITION OF DATA PRODUCTS

For the context of this work, data products refer to potentially valuable datasets, either processed or raw, offered for purchase primarily to support business decisions. This definition incorporates the views of Yu and Zhang (2017), who define data products as datasets subjected to processes like cleaning, formatting, or encrypting, and Fruhwirth, Breitfuss, and Pammer-Schindler (2020) and Driessen et al. (2022), who respectively emphasize on the value data products provide to customers and the optimization of data assets for trade.

Nevertheless, certain adjustments are made to cater to the specific focus of this study, which is pricing mechanisms for data products. Free data products, such as those provided by governmental organizations, are excluded as they do not involve monetary exchange. Also, data products aimed at end-users, e.g. normal persons, are deemed out of scope for this work.

Therefore, this study limits the definition of data products to those traded either business-to-business (B2B) or person-to-business (P2B). The precise form of accessibility is not considered within the scope of this work; the primary factor is the intention to use these data assets for a specific purpose. In addition, data assets need to be shareable to become data products. Formats of sharing are not considered.

With these considerations, we define data products as potentially valuable data assets, offered by companies or individuals in exchange for monetary compensation.

3.2. DEFINITION OF DATA MARKETPLACES

Though research on data marketplaces is burgeoning, a universally accepted definition remains hard to find (Stahl et al., 2016). However, various authors provide definitions encompassing elements relevant to this study. Driessen et al. (2022) offer a broad definition, describing data marketplaces as platforms providing the necessary infrastructure and services to facilitate data products' exchange between providers and consumers. Other authors emphasize functions such as user registration, dataset upload and maintenance, data access regulation via different licensing models, and services for dataset location and vendor access (Schomm et al., 2013).

Data marketplaces, by offering standardized interfaces and services, streamline interactions between multiple actors (Spiekermann, 2019). Yu and Zhang (2017) highlight another significant characteristic: the offering of data products at reasonable prices, which is crucial for this study.

The key actors involved in a data marketplace ecosystem include data providers, data buyers, and marketplace owners (Spiekermann, 2019). Data providers, individuals, or companies, offer data products on the marketplace, expecting to generate revenue. Data providers can also be the data products' owners or creators, but this is not necessarily the case (Driessen et al., 2022). On the other hand, data buyers select data products aligning with their requirements and willingness-to-pay (Fruhwirth, Rachinger, & Prlja, 2020). Commercial data buyers, such as analysts, application vendors, data-associated algorithm developers, and consultants, are the primary focus of this paper (Muschalle et al., 2012). Marketplace owners, or data brokers, act as intermediaries, potentially charging fees for platform usage (Driessen et al., 2022; Spiekermann, 2019). However, the detailed business models of data brokers are beyond this study's scope. Examples of such data marketplaces include Datarade, Snowflake, and Advaneo.

3.3. INTERACTIONS ON DATA MARKETPLACES

The following figure illustrates the model underlying the understanding of the data marketplace ecosystem. Each shown role is described in the afterwards.

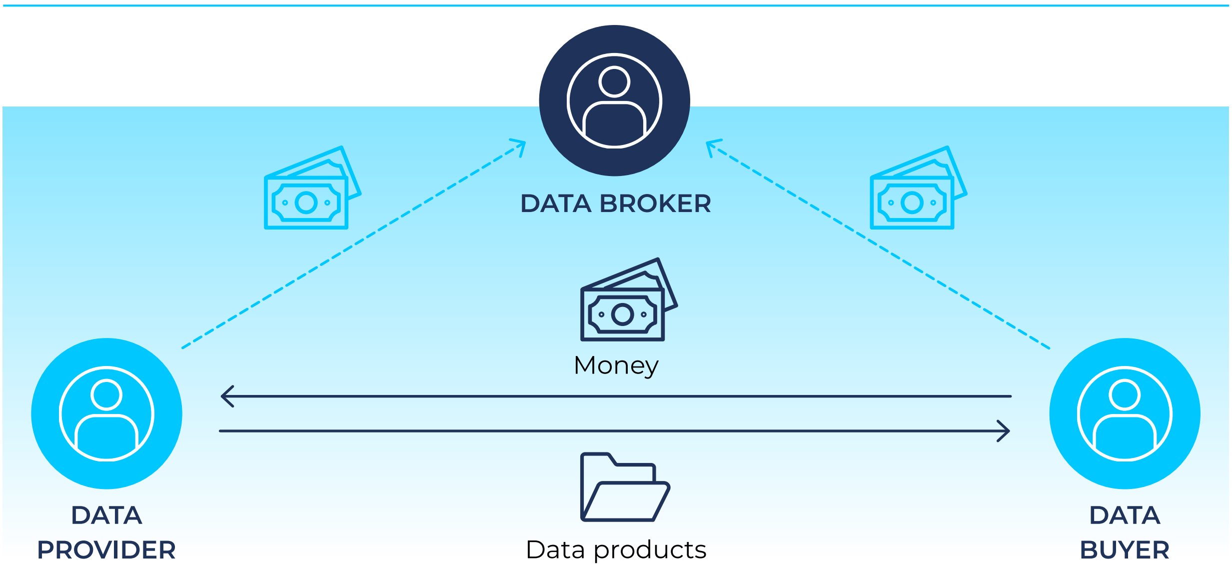

Figure 1: The data marketplace ecosystem

Data Provider: A data provider is an entity, either an individual or a company, that offers data products on the data marketplace. The expectation of a data provider is to generate revenue from these transactions. They can also be the creators or owners of the data products, but this is not a mandatory requirement. Data providers upload their datasets onto the marketplace and manage them for potential consumers.

Data Broker (Marketplace Owner): A data broker, also referred to as the data marketplace owner, plays an intermediary role in the data marketplace ecosystem. They host the marketplace and provide a platform for data providers and data buyers to interact and conduct transactions. The data broker collects and hosts data products from providers and assists data buyers in finding appropriate products for their needs. Depending on the marketplace's business model, data brokers may charge fees to data providers or data buyers for using the platform.

Data Buyer: A data buyer, or a data consumer, is an entity that selects and purchases data products that meet their specific requirements and align with their willingness-to-pay. They pay the demanded price to the data provider and get access to their purchased data in different ways.

4. Pricing mechanisms for data products in the scientific literature

A systematic review of literature was performed in line with Denyer and Tranfield's (2011) five-step procedure. The steps go from locating, selecting relevant studies, evaluating, analyzing and synthesizing, and present them. The paper moves to presenting the results directly, as the method is commonly known and establishes as one of the standard methods. This section concentrates on the analysis of various pricing mechanisms for data products as highlighted in the existing literature, which is central to the RQ. Several pricing mechanisms were identified and categorized based on the literature review.

Fricker and Maksimov (2017) contribute significantly to the body of knowledge, organizing the explored literature into three pricing mechanism categories for data products: single requests, volume packages, and time-based subscriptions. Single requests entail pricing mechanisms with metrics related to usage and requests, such as pay-per-use, pay-per-unit, pay-per-query, and customer-proposed prices. Volume packages offer a predetermined data amount at a set price. Time-based subscriptions provide customers unlimited access to data sets within a specific period for a fixed fee (X. Li et al., 2017).

Our study extends the categories from Fricker and Maksimov (2017), incorporating two additional pricing mechanism categories. Muschalle et al. (2012) offer more depth by outlining another primary category derived from interviews with seven data providers: free data. However, given this work's focus on pricing, free data is not considered a relevant category. They further detail two models that combine elements of previously mentioned ones: two-part tariffs and freemium models. Two-part tariffs integrate two different pricing models – a basic fixed fee coupled with an additional price for each unit consumed, whereas the freemium model provides basic services for free, charging only for premium services.

The literature is categorized into five categories each for mechanisms and approaches. For ease of reading, the following table gives an overview. A checkmark in a cell indicates that literature was found on that specific topic.

Pricing mechanism/ Pricing approach	Single requests	Volume packages	Time-based subscriptions	Two-part tariffs	Freemium
Pricing function	✓		✓		
Game theory	✓		✓	✓	
Auction	✓	✓			
Theoretical/ Conceptual	✓		✓		
In practice	✓			✓	✓

Table 1: Pricing mechanisms and approaches in the literature

4.1. SINGLE REQUEST PRICING WITH PRICING FUNCTIONS

This section covers different approaches for single requests using pricing functions.

Automatic pricing based on request complexity: Here we find the approach of Koutris et al. (2012) which is considered pioneering work in the field of data-based pricing. This method makes it possible to set prices automatically based on some predefined views, which overcomes the limitations of explicitly priced views. Pricing is based on the complexity of the requests, with each request considered as a version of the data product.

Flexible pricing by taking into account the request history: In a continuation of their approach, Koutris et al. (2013) present QueryMarket, a flexible pricing system that takes into account the query history of data buyers to avoid duplicate calculations and incorporate updates and overlapping information.

Fine-grained pricing options for data requests: C. Li and Miklau (2012) address the limitations of current data marketplaces that do not provide fine-grained pricing models and propose pricing functions for detailed pricing, including inductive and deductive pricing approaches as well as conditional pricing.

Privacy-oriented pricing: Another approach is presented by C. Li et al. (2017), who propose a pricing function for private data to compensate data providers for the loss of privacy without compromising data quality.

Customizable and response-dependent pricing models: Lin and Kifer (2014) criticize the limited choice of queries in traditional pricing models and introduce pricing models that cover a wide range of queries, including instance-independent, pre-dependent, and delayed pricing.

Real-time pricing for aggregated requests: With QIRANA, Deep and Koutris (2017) present a scalable, real-time pricing system for data queries that supports aggregated queries and enables fast pricing through predefined pricing functions.

Pricing based on minimal provenance: Tang et al. (2013) and Y. Shen et al. (2019) develop pricing models based on the minimum set of tuples used to answer a query to achieve higher granularity in pricing.

Efficiency and algorithms for pricing functions: Chawla et al. (2019) and Wang et al. (2018) explore various pricing functions and algorithms to increase the efficiency of pricing and achieve an optimal balance between price and execution time.

Consideration of the intrinsic data value: X. Li et al. (2017) and Z. Zhang et al. (2021) criticize approaches that assign the same price to each data item and propose mechanisms that consider the intrinsic value of the data.

4.2. SINGLE REQUEST PRICING WITH GAME THEORY APPROACHES

In the following, the use of game theory approaches in individual demand pricing for data products is presented. Game theory, a method for analyzing strategic interactions between (rational) decision makers, provides a rich framework for the development of pricing mechanisms in private data markets. By applying various game theory concepts, researchers develop models that aim to find equilibria that balance the interests of all participants.

Application of the Rubinstein bargaining: Jung et al. (2019) use Rubinstein bargaining to determine data pricing and noise levels in a framework for private data markets. This approach makes it possible to find a price that reflects the preferences of both parties through repeated bids and counterbids between data providers and buyers.

Development with evolutionary game theory: Xiong and Zheng (2019) use evolutionary game theory to develop a model for pricing data products. Here, the data provider sets the price and value level, while the data buyer's purchase decision depends on a utility function. This approach reflects the dynamic adaptation of strategies over time, based on the success of past decisions.

Stackelberg game approaches: Several studies adopt the Stackelberg game approach to data pricing, with the aim of establishing a Nash equilibrium that balances the interests of all stakeholders.
Xiao et al. (2021) investigate the optimal pricing of raw data and subscription fees in a big data market, where a service provider processes and sells data to subscribing users.

M. Zhang et al. (2019) propose a quantity-based pricing mechanism for data updates, where the price of fresh data depends on the number of updates previously purchased by the buyer.

Blockchain-based and IoT data markets: Liu et al. (2019) develop a pricing mechanism for an IoT data market enhanced by blockchain technology using the Stackelberg game framework. They compare two pricing mechanisms - one that takes competitors' pricing into account and one that does not - and demonstrate through numerical simulations that competitive pricing leads to higher utility and profit for data buyers and providers.
B. Shen et al. (2019) present a model for the pricing of Internet of Vehicles data, where data providers sell raw data to buyers and service providers process the data on their behalf.
Xu et al. (2020) analyze optimal pricing in a blockchain-based vehicle data market using a Stackelberg game approach. Data providers determine the pricing for raw data, and service providers process the data and set prices for the processed data. The data buyer selects the data product and size to purchase, and all actors adopt optimal pricing or purchasing strategies to maximize their utilities.

4.3. SINGLE REQUEST PRICING WITH AUCTION MECHANISMS

In the area of individual demand pricing through auction mechanisms, the work of various authors and research groups offer different approaches.

Sealed bid auction for data bundles: Luo et al. (2020) propose a sealed-bid auction model for big data pricing, where buyers bid their evaluation value on data bundles.

Auction mechanism for request pricing: Wang et al. (2019) design an auction mechanism for query pricing, allowing flexible resource allocation and higher social welfare.

Auction-based pricing for time-critical data: Zhao et al. (2020) propose auction-based pricing mechanisms for highly time-sensitive data, considering both random and deterministic relationships between value and time. Experimental results demonstrate the stability, efficiency, truthfulness, and profitability of these auction mechanisms.

4.4. THEORETICAL AND CONCEPTUAL APPROACHES FOR SINGLE REQUEST PRICING

In the area of theoretical and conceptual approaches, various studies have been identified.

Blockchain-based peer-to-peer marketplaces: La Vega et al. (2018) propose a distributed peer-to-peer marketplace architecture based on blockchain technology. The pricing mechanisms used are similar to those of centralized data marketplaces and include one-time payments, recurring payments and usage-based payments.

Approaches for view- and request-based pricing: Tang et al. (2015) present a model in which predefined views with fixed prices are used to determine the cost of a request, enabling transparent and predictable pricing.

Genetic algorithms for price setting: Yu and Zhang (2017) use a genetic algorithm to price data, allowing the platform owner to determine the number of data product versions, their quality and price.

Comparison of fixed price and flexible pricing: Q. Li et al. (2021) compare fixed pricing, where a dataset is sold at a predetermined price, with flexible pricing, where buyers are charged usage costs based on the data subset they use.

Measure theory-based pricing framework: Ye et al. (2021) propose a measure theory-based pricing framework that addresses the lack of appropriate measurements for data products by using mathematical tools to measure dataset sizes and allowing flexibility in pricing.

Differential privacy query pricing mechanisms: Y. Shen et al. (2022) present two query pricing mechanisms for personal big data trading based on differential privacy: Positive pricing and reverse pricing, each of which takes different approaches to compensate for privacy losses.

Pricing framework for the food production industry: Rix et al. (2021) present a design framework for pricing data products in the food production industry and recommend one-time payments or subscription models for data products that combine raw data with analytical services.

Model for pricing tuples of Big Personal Data: Y. Shen et al. (2016) criticize existing pricing models for intangible goods and propose a model based on various data attributes that influence data value to enable accurate, fair and reasonable pricing.

4.5. SINGLE REQUEST PRICING IN PRACTICE

In the practical context of individual demand pricing, various studies develop specific models and approaches that are applied in real markets, especially in the automotive industry.

Business model taxonomy for data marketplaces in the automotive industry: Bergman et al. (2022) develop a business model taxonomy specifically for data marketplaces in the automotive industry. They identify different pricing models, including usage-based models, freemium models and commission systems. The distinction between fixed pricing mechanisms and dynamic pricing strategies is particularly emphasized. Interestingly, the authors find that none of the data marketplace operators studied use dynamic pricing models, indicating a preference for predictable and stable pricing structures.

Analysis of the pricing mechanisms of data providers: Mehta et al. (2021) conduct a detailed analysis of the pricing mechanisms of four data providers and discuss the optimality of price-quantity schemes. They see a particular challenge in setting appropriate prices that take into account the heterogeneity in buyers' valuations. The authors numerically demonstrate the advantages of two-part tariffs and two-block tariffs for uniform data sets, where the price depends solely on the quantity purchased.

4.6. PACKAGE PRICING

There is one study identified in the context of package pricing.

Ascending auction for crowdsensing data: Feng et al. (2021) design a method where data buyers can bid for the data packets they are interested in. The optimal allocation and trading prices are calculated based on a provided algorithm. The iteration ends when neither the optimal allocation nor the prices change in two consecutive rounds, and the buyers in the last round pay their final bid prices.

4.7. SUBSCRIPTION-BASED PRICING

In the area of subscription-based pricing, various studies are developing models and approaches to meet the challenges of pricing in big data markets.

Development of a pricing model based on data quality: Yang et al. (2019) develop a pricing model for big data based on a utility function of data quality. This allows data brokers to adjust quality levels and subscription fees to maximize their profit. Experiments with real data sets confirm the applicability of the proposed price function. Also see Xiao et al. (2021) in the single request pricing section.

Game-theoretic approaches to analyze data prices: M. Zhang et al. (2021) design a Stackelberg game in which the data provider decides a pricing scheme and the data buyer subsequently sets a cost-minimizing update schedule. A one-time subscription fee is charged, and the price per data update remains constant. The authors consider both a finite and an infinite horizon for comparing the pricing mechanisms. While experiments show that volume-based pricing is only optimal with a finite horizon, the subscription-based pricing model works optimally in both scenarios.

Conceptual work on subscription-based pricing models: B. Li et al. (2022) argue against time-consuming price calculations in request-based models. Given the constant demand of many data buyers, they propose a preset subscription scheme that considers an upper bound for data products. The model, which includes both linear and sub-linear willingness-to-pay functions, is shown to be theoretically always solvable and applicable in a real market scenario. Also see La Vega et al. (2018) and Rix et al. (2021) who propose mechanisms that include single-request pricing.

4.8. TWO-PART TARIFF PRICING

Several approaches have been identified in the context of pricing models for data products.

Two-part pricing model: M. Zhang et al. (2021) propose a pricing model that includes a one-time subscription fee and a constant price per data update. This structure makes it possible to generate both initial and ongoing revenue from the sale of data products.

Multiple combinatory options: Mehta et al. (2021) emphasize that both two-part tariffs and two-block tariffs are optimal mechanisms for pricing uniform datasets.

Hybrid pricing mechanisms in the peer-to-peer data market: Zeng et al. (2018) develop a model for a peer-to-peer market for sensor data that provides for a hybrid pricing mechanism. This consists of a fixed price and a variable price factor that is related to the revenue that a buyer generates with the acquired data. Evolutionary game theory is used to analyze market development and calculate the equilibrium.

4.9. FREEMIUM PRICING

Two studies were identified research freemium models.

Use of freemium models: Bergman et al. (2022) discover through interviews with operators of data marketplaces that freemium models are being used.

Specific examples of freemium models: Schomm et al. (2013) describe specific applications of the freemium model. Factual enabled up to 10,000 API calls per day free of charge, while fees were charged per use for each additional call. The CloudMade Data Market Place offered a combination of a free trial period and a flat rate model.

4.10. OTHER WORK ON PRICING MECHANISMS FOR DATA PRODUCTS

Several studies explore literature that identify pricing models that did not fit into the created matrix from this chapter.

Usage or request-based pricing models: Fricker and Maksimov (2017) conduct a systematic literature review on data pricing, focusing mainly on usage or query-based pricing models. They find a discrepancy between research and practice and argue for more research in real-world use cases.

Economy-based and game theory-based models: Liang et al. (2018) classify pricing models for data products into two categories: economy-based and game theory-based models. They discuss price discrimination and dynamic pricing and emphasize that competitive markets can drive data prices to adjust to marginal costs. Busch-Casler and Radic (2022) conduct a narrative review and conclude that there is not yet a consensus on an optimal pricing mechanism for data products. They find that market pricing is most commonly discussed, but that these discussions are predominantly theoretical, often using game-theoretic approaches, and that many papers deal with technical models and provide pricing algorithms.

Query-based pricing in data marketplaces: Abbas et al. (2021) conduct a systematic literature review on data marketplaces and note that the literature is dominated by technical research, which includes query-based pricing. The authors also note that data marketplaces are rarely used commercially.

5. Conclusion and Future Research

As the importance of data in the business sector grows, so does the need for effective data pricing mechanisms. This work, building on the literature review by Fricker and Maksimov (2017), integrates a systematic literature review with empirical insights to enhance understanding of data product pricing. The review focuses on the pricing mechanisms most discussed in the literature, with single-request pricing – encompassing pay-per-use, pay-per-unit, and pay-per-query models – identified as the most addressed mechanism. Query-based pricing receives substantial attention due to its complexity, while time-based subscriptions, two-part tariffs, freemium models, and volume packages are less examined. Authors frequently employ pricing functions and game-theory approach in theoretical or conceptual investigations, with some also exploring auction-based pricing. However, real-world insights are limited, often leading to the use of approximations due to the computational demands of proposed algorithms.

This work offers a basis for future research to explore the managerial perspective of data product pricing and the pricing of data products with varying perceived value among buyers. As data differs significantly from tangible products – mainly because of its near-zero marginal cost for replication – it necessitates a nuanced understanding of pricing beyond mere cost considerations. Therefore, future research could seek to identify various factors influencing data product pricing through a combined approach of systematic literature review and expert interviews. Additionally, given the historical challenges of profitability for many data marketplaces, the exploration of practical pricing mechanisms could provide invaluable insights, linking theory with practice and offering new perspectives on what works in the real world.

This research bases on data collected in a literature review that went on from May 2022 to June 2022 and therefore not contains more recent insights.

Author
Dr. Mashood Ahmad, Senior Consultant for Data & Analytics and AI,
Camelot Management Consultants
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CONTACT

CAMELOT Management Consultants

Dr. Mashood Ahmad | Senior Consultant for Data & Analytics and AI | mahm@camelot-mc.com | Camelot Management Consultants

Camelot Management Consultants · www.camelot-mc.com · office@camelot-mc.com

EUROPE
Global Headquarters
Theodor-Heuss-Anlage 12
68165 Mannheim
Germany

Phone +49 621 86298-0

AMERICAS
100 W. Sixth Street
Suite 103
Media · PA 19063
USA

Phone +1 267 589 9242

MIDDLE EAST
Jumeirah Lakes Towers
Cluster O · Reef Tower
P.O. Box 5003333 · Dubai
United Arab Emirates

Phone +971 4 350 7441

ASIA/PACIFIC
97 Varsha · Plot no. 96/2+97
CTS no. 1132-1133 · Anand Park
Aundh · Pune · MH
India 411007

Phone +91 9987 987 385

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