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The Economics of Data Science in Logistics: Information Costs, Data Assets, and Competitive Advantage

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Abstract
Data science is widely presented in the logistics literature as a set of analytical techniques, yet the decision to build a data science capability is fundamentally an economic one: firms collect, clean, integrate, and analyze operational data because doing so is expected to lower the cost of coordinating under uncertainty, raise the productivity of existing assets and decisions, or create a data resource that rivals cannot easily replicate. This paper adopts a conceptual approach, grounded in transaction cost economics, the information processing view of organization design, the resource-based view, and the economics of data and information technology, to examine why and where data science creates economic value in logistics operations. We propose a framework linking three economic mechanisms, information-cost economizing, productivity growth from data-driven decision-making and its complementary organizational investments, and resource-based advantage from proprietary data assets, to the descriptive, predictive, and prescriptive layers of logistics analytics and to inter-firm data sharing. The framework treats data quality as a cross-cutting cost that conditions every mechanism, and it considers the labor-market implications of data science in logistics, distinguishing the planning and reporting tasks that analytics displaces from the new tasks of data engineering, data governance, and analytical translation that it creates. By treating data as an economic asset with distinctive properties, notably nonrivalry and dependence on quality, rather than as a by-product of operations, the study offers logistics economists and managers a structured basis for evaluating when investment in data science is likely to pay off, and provides a conceptual foundation for future empirical research on the productivity, competitive, and labor-market effects of data-driven logistics.

Keywords: Data Science, Logistics Economics, Transaction Cost Economics, Resource-Based View, Data Quality, Data-Driven Decision-Making

1. Introduction

Logistics management is, at its core, an economic problem: firms must decide how to organize the flow of goods, information, and resources so as to minimize the combined costs of transacting, coordinating, and holding inventory across organizational boundaries (Mentzer *et al*., 2001) [1]. Each of these costs is, in large part, a cost of not knowing: inventory is held because future demand is uncertain, vehicles are dispatched with slack because travel times are uncertain, and partners renegotiate because neither side can fully observe the other. The rapid growth of transactional, sensor, and location data in logistics networks has therefore raised an economic question as much as a technical one, namely how much of this uncertainty can profitably be reduced by systematically extracting knowledge from data (Waller & Fawcett, 2013) [2].

Data science is typically introduced in the logistics literature as a toolkit of statistical and computational methods, yet its adoption is better understood as an investment decision governed by ordinary economic logic. From a transaction cost perspective, data science lowers the cost of coordinating decisions under uncertainty and bounded rationality by replacing costly monitoring, negotiation, and buffer capacity with shared, analyzable information (Williamson, 1981) [3]. From a resource-based perspective, a firm's accumulated operational data, together with the routines and skills used to analyze it, can constitute a resource that is valuable, rare, and difficult to imitate, and therefore a source of sustained competitive advantage rather than a commodity (Barney, 1991) [4].

However, the economics of information technology cautions against treating investment in data infrastructure and analytics as automatically productive. Firm-level evidence shows that the returns to computerization depend on complementary, often

intangible, organizational investments in skills, process redesign, and decision rights, and that these returns can take years to materialize (Brynjolfsson & Hitt, 2000) [5]. Applied to logistics, this implies that the economic value of data science cannot be read off the volume of data collected or the sophistication of the analytics; it depends on whether the resulting insights change the decisions that planners, dispatchers, and managers actually make.

A further economic dimension concerns labor. Data science in logistics automates specific tasks, such as manual report preparation, routine forecasting, and spreadsheet-based planning, which economic theory predicts will displace labor from those tasks; at the same time, it creates new tasks in data engineering, data quality assurance, and the translation of analytical results into operational decisions, partially reinstating labor demand (Acemoglu & Restrepo, 2019) [6]. Most existing studies of data science and big data analytics in logistics classify techniques and application areas (Wang *et al*., 2016) [11]; (Nguyen *et al*., 2018) [12], or survey adoption and skills among practitioners (Schoenherr & Speier-Pero, 2015) [18], leaving the cost, competitive, and labor-market dimensions comparatively underexamined.

This paper adopts a purely conceptual approach, grounded in transaction cost economics, the information processing view, the resource-based view, and the economics of data and information technology, to examine why and where data science creates economic value in logistics. Drawing on principles of theoretical contribution (Whetten, 1989) [23], we propose a framework linking these economic mechanisms to the layers of logistics analytics, thereby providing a foundation for future empirical and applied research on the economics of data-driven logistics.

2. Background

Data science can be defined as a set of principles, processes, and techniques for extracting knowledge from data in support of decision-making; it sits between the technologies that store and process large data sets and the managerial practice of data-driven decision-making that ultimately creates value (Provost & Fawcett, 2013) [7]. In supply chain management, Waller and Fawcett (2013) [2] argue that data science requires both quantitative skill and domain knowledge of logistics processes, since the questions worth asking of the data, and the interpretation of the answers, are rooted in the economics of inventory, transport, and coordination. This definition matters economically because it locates the source of value not in data volume as such but in the chain that runs from data, through analysis, to a changed decision.

Transaction cost economics offers one lens for understanding why firms invest in this chain. Williamson (1981) [3] argues that governance structures are chosen to economize on the costs of coordinating transactions under uncertainty and bounded rationality. Logistics transactions are information-intensive: carriers, warehouses, suppliers, and customers must align plans that each party can only partially observe. Data science can be read as an instrument for economizing on these costs: by converting dispersed records of orders, shipments, and asset status into shared measures and forecasts, it lowers the cost of monitoring partners, detecting deviations, and adapting plans without resorting to renegotiation or to the vertical integration that would otherwise be needed to secure information.

The information processing view of organization design sharpens this argument. Galbraith (1974) [8] explains organizational form as a response to task uncertainty: as uncertainty rises, organizations must either reduce their need for information, for example by holding slack resources such as extra inventory or longer lead times, or increase their capacity to process information, for example through vertical information systems and lateral coordination. In logistics, safety stock, buffer fleet capacity, and generous delivery windows are precisely such slack resources. Data science is an investment on the other side of Galbraith's choice: it raises information processing capacity, and its economic payoff is the slack that can be released once uncertainty is better measured and anticipated.

A second lens is the resource-based view of the firm, which holds that sustained competitive advantage arises from resources that are valuable, rare, and costly for rivals to imitate (Barney, 1991) [4]. Analytical software and cloud infrastructure are widely available and therefore rarely a source of lasting advantage. What is rarer is the combination of a firm's proprietary operational data, accumulated over years of shipments and orders, with the human skills and data-driven culture needed to act on it. Gupta and George (2016) [16] formalize this as a big data analytics capability built from tangible resources (data, technology, and basic investment), human resources (technical and managerial skills), and intangible resources (a data-driven culture and organizational learning), and show that this capability is associated with superior firm performance.

Data also has economic properties that distinguish it from conventional capital. Jones and Tonetti (2020) [9] emphasize that data is nonrival: the same data set can be used by many firms or functions simultaneously without being depleted, which generates increasing returns and implies that broad use of data can produce large social gains. The same analysis shows that firms may choose to hoard data rather than share it, leading to its inefficient use. Both properties are directly relevant to logistics, where a single shipment record is simultaneously useful to the shipper, the carrier, the consignee, and the port or warehouse operator, yet is frequently held in incompatible systems by each.

Data science further depends on an infrastructure that is itself a capital investment. Research on the Internet of Things in supply chain management documents how connected sensors provide the continuous streams of location, temperature, vibration, and throughput data on which logistics analytics depends (Ben-Daya, Hassini & Bahroun, 2019) [20]. The economic value of these streams is, however, conditioned by their quality. Hazen *et al*. (2014) [10] identify data quality, along dimensions such as accuracy, timeliness, completeness, and consistency, as a distinct problem for data science in supply chain management and propose statistical process control methods for monitoring and controlling it. Poor-quality data is not merely a technical nuisance: decisions taken on inaccurate or stale data can be more costly than decisions taken on no data at all, because they are acted upon with unwarranted confidence.

Finally, data science has direct implications for the demand for logistics labor. Economic theory on automation distinguishes a displacement effect, in which technology takes over tasks previously performed by workers, from a reinstatement effect, in which new tasks are created in which labor holds a comparative advantage (Acemoglu &

Restrepo, 2019) [6]. In data-driven logistics, routine reporting and rule-based forecasting are displaced, while data engineering, data stewardship, and the interpretation of analytics for operational decisions are created. Survey evidence that supply chain organizations struggle to find professionals combining analytical skill with domain knowledge (Schoenherr & Speier-Pero, 2015) [18] suggests that the reinstatement side of this balance is economically significant.

3. Literature Review

Foundational logistics research defines the field as the planning and control of the flow of goods and related information to meet customer requirements (Mentzer *et al*., 2001) [1]. Within this tradition, the economic cost of poor information has long been recognized. Lee, Padmanabhan and Whang (1997) [15] show that orders passed upstream in a supply chain distort the underlying demand signal, so that the variance of orders exceeds that of sales and grows as one moves upstream, the bullwhip effect, and they attribute it to demand signal processing, order batching, price variations, and rationing games. Their analysis identifies the sharing of point-of-sale demand data as a remedy, and it is, in economic terms, one of the clearest early demonstrations that the value of logistics data lies in reducing the costs created by information asymmetry between firms.

The broader management literature on analytics developed in parallel. Davenport (2006) [14] describes firms that compete on analytics, arguing that when products and technologies are similar across competitors, business processes are among the few remaining sources of differentiation, and that analytics competitors are distinguished by senior leadership that treats analytics as central to strategy. Chen, Chiang and Storey (2012) [13] trace the evolution of business intelligence and analytics from reporting and statistical methods to the analysis of large, unstructured, and sensor-based data, and propose a framework of applications and research directions. Provost and Fawcett (2013) [7] position data science as the connective tissue between data-processing technologies and data-driven decision-making, cautioning that confusion about its definition risks turning it into a buzzword rather than a discipline.

Within logistics and supply chain management specifically, Waller and Fawcett (2013) [2] propose definitions of data science and predictive analytics for the field and call for research on the skills needed by supply chain data scientists. Schoenherr and Speier-Pero (2015) [18] report one of the largest surveys of predictive analytics use among supply chain professionals, documenting current use, motivations, perceived benefits, and barriers, together with the skills organizations seek in data scientists. Fosso Wamba *et al*. (2015) [19] combine a systematic review with a longitudinal case study to examine how big data generates business value, while Wang *et al*. (2016) [11] classify the application of big data business analytics in logistics according to the level of analytics, descriptive, predictive, or prescriptive, and the strategic or operational focus of the decision, proposing a maturity framework that progresses from functional to process-based, collaborative, agile, and sustainable supply chain analytics. Nguyen *et al*. (2018) [12] extend this classification by mapping where in the supply chain big data analytics has been applied, at what level of analytics, with which model types, and with which techniques.

A second stream examines the conditions under which data investment pays off. Hazen *et al*. (2014) [10] argue that the data quality problem has been underexamined in supply chain research despite its consequences for decisions, and they bring quality-control theory to bear on it. Gupta and George (2016) [16], drawing on resource-based theory, show that analytics capability is a bundle of complementary resources rather than a technology purchase. At the economy-wide level, Brynjolfsson and McElheran (2016) [17] document that the share of U.S. manufacturing plants practicing data-driven decision-making nearly tripled, from 11% to 30%, between 2005 and 2010, and that adoption is concentrated in plants with greater size, information technology, educated workers, and prior learning, which are precisely the complementary assets predicted by the economics of information technology (Brynjolfsson & Hitt, 2000) [5].

A third stream, largely developed outside logistics, examines data itself as an economic good. The nonrivalry of data, and the resulting tension between the social gains from broad use and the private incentive to hoard, provides a theoretical basis for analyzing data sharing among supply chain partners (Jones & Tonetti, 2020) [9]. The forecasting literature adds a note of caution about the returns to analytical sophistication: comparative evidence shows that more complex models do not always outperform simpler statistical methods, while requiring greater computational resources (Makridakis, Spiliotis & Assimakopoulos, 2018) [21], a finding that is itself an economic result about the cost of complexity relative to the accuracy gained.

Taken together, this literature provides substantial evidence that data science, predictive analytics, and big data are relevant to logistics, and well-developed classifications of where and how they are applied. Once an economic lens is applied, however, a gap appears. The classification literature (Wang *et al*., 2016) [11]; (Nguyen *et al*., 2018) [12] describes application areas but rarely connects them to the cost of information, the complementary investments required, or the competitive durability of the resulting advantage, while the economics literature on data (Jones & Tonetti, 2020) [9] and on data-driven decision-making (Brynjolfsson & McElheran, 2016) [17] has seldom been applied to logistics operations. This leaves open the question of when, economically, investment in a given layer of logistics data science is justified.

4. Analysis and Discussion

The proposed framework organizes data science in logistics around three economic mechanisms, information-cost economizing, productivity from data-driven decision-making and its complementary investments, and resource-based advantage from proprietary data, and evaluates each against two further dimensions: data quality, which acts as a cost that conditions every mechanism, and labor, which captures the displacement and reinstatement of tasks. Rather than asking only whether a given analysis is technically sound, the framework asks which mechanism it activates, and at what cost, across four layers of logistics data science: descriptive analytics and visibility, predictive analytics, prescriptive analytics, and inter-firm data sharing (Wang *et al*., 2016) [11].

In descriptive analytics and visibility, the dominant mechanism is information-cost economizing. Dashboards, shipment tracking, and performance measurement integrate data from transport management, warehouse management, and sensor systems to show where goods and assets are and how processes are performing (Ben-Daya, Hassini & Bahroun, 2019) [20]. In transaction cost terms, this lowers the cost of monitoring carriers and partners and of detecting deviations early, reducing the need for costly inspection or renegotiation (Williamson, 1981) [3]. In information processing terms, it is an investment in vertical information systems that raises the organization's capacity to handle exceptions without escalating every one through the hierarchy (Galbraith, 1974) [8]. Descriptive analytics is the least technically demanding layer, yet its economic value is often underestimated because the benefits appear as avoided costs rather than as visible gains.

In predictive analytics, the mechanism shifts toward productivity from data-driven decision-making. Forecasts of demand, transit times, arrival times, and equipment failures allow inventory, labor, and capacity to be committed against expected rather than worst-case conditions, releasing the slack resources that Galbraith (1974) [8] identifies as the alternative to information processing. The productivity gain, however, materializes only when planning processes and decision rights are reorganized around the predictions (Brynjolfsson & Hitt, 2000) [5]; a forecast that is generated but overridden by habit produces cost without benefit. The comparative evidence of Makridakis, Spiliotis and Assimakopoulos (2018) [21] adds that the economically optimal level of model complexity depends on the structure of the data, so that the cost of building and maintaining a model must be weighed against its marginal accuracy over simpler alternatives.

In prescriptive analytics, which recommends decisions such as inventory policies, network configurations, and transport plans, resource-based advantage becomes more prominent alongside cost economizing. Because prescriptive models are calibrated on a firm's own cost structure, network, and historical outcomes, the resulting decision logic is firm-specific and costly for competitors to replicate even when they have access to the same optimization software (Barney, 1991) [4]. Consistent with Gupta and George (2016) [16], the advantage resides less in the algorithm than in the bundle of proprietary data, analytical talent, and a culture in which managers act on model recommendations. Davenport's (2006) [14] observation that analytics competitors differentiate through their processes rather than their products applies with particular force here.

In inter-firm data sharing, the economics of data as a nonrival good becomes central. Shared point-of-sale, inventory, and shipment data can dampen the bullwhip effect by giving upstream members access to the true demand signal rather than distorted orders (Lee, Padmanabhan & Whang, 1997) [15]. Because data is nonrival, the same data set can create value for every partner simultaneously, which implies large joint gains from sharing (Jones & Tonetti, 2020) [9]. Yet each firm also has an incentive to hoard data that underpins its own advantage, and transaction cost economics predicts that sharing will be limited where partners fear opportunistic use of what they disclose (Williamson, 1981) [3]. The resulting tension between joint value and private appropriation explains why inter-firm data sharing in logistics often lags what is technically feasible, and why governance arrangements, contracts, platforms, or industry standards, are as important as analytical tools in realizing its value.

Across all four layers, data quality operates as a cost that conditions each mechanism. Information-cost savings disappear if tracking data is late or incomplete; productivity gains from prediction reverse if forecasts are trained on inconsistent records; resource-based advantage erodes if the proprietary data set is unreliable; and partners will not share data whose accuracy they cannot verify (Hazen *et al*., 2014) [10]. Economically, data quality management is therefore not an overhead to be minimized but a complementary investment of the kind emphasized by Brynjolfsson and Hitt (2000) [5], without which the returns to other data science investments cannot be realized.

The labor-market dimension runs in parallel to these cost and productivity effects. Descriptive and predictive analytics displace manual data collection, report compilation, and rule-of-thumb forecasting, while creating reinstatement tasks in data engineering, data stewardship, quality monitoring, and the translation of analytical outputs into operational action (Acemoglu & Restrepo, 2019) [6]. The survey evidence of Schoenherr and Speier-Pero (2015) [18] and the call by Waller and Fawcett (2013) [2] for supply chain data scientists who combine quantitative skill with domain knowledge suggest that the scarce input is not computation but people able to connect data to logistics decisions. The adoption pattern documented by Brynjolfsson and McElheran (2016) [17], in which data-driven decision-making spreads first among firms with educated workers, reinforces the point that human capital is a binding complement.

A key analytical implication of viewing these layers through the same set of economic mechanisms is that they are not independent. Prescriptive models depend on predictive inputs, which depend on descriptive data pipelines, which depend in turn on data quality and, increasingly, on data shared by partners. An investment at one layer may therefore yield little until the layers beneath it are in place, and the economic return to the system as a whole may exceed the sum of returns evaluated layer by layer. This interdependence is consistent with research showing that the performance effects of supply chain integration depend on the configuration of internal, supplier, and customer integration rather than on any single dimension in isolation (Flynn, Huo & Zhao, 2010) [22]. For logistics managers and economists, the implication is that data science investments are best evaluated as a portfolio sequenced along the analytics maturity path, from functional visibility toward collaborative and agile analytics (Wang *et al*., 2016) [11], rather than as stand-alone projects judged on immediate technical performance.

5. Conclusion and future works

This study examined data science in logistics as an economic, rather than a purely technical, phenomenon. By linking transaction cost economics, the information processing view, the resource-based view, and the economics of data and information technology to the descriptive, predictive, and prescriptive layers of logistics analytics and to inter-firm data sharing, the proposed framework moves beyond a classification of data science applications toward an account of why and when investment in data pays off. Consistent with foundational logistics

theory (Mentzer *et al*., 2001) [1], the framework offers a coherent basis for future empirical and applied investigation. The primary contribution of this study lies in connecting the logistics literature on data science and big data analytics (Waller & Fawcett, 2013) [2]; (Wang *et al*., 2016) [11]; (Nguyen *et al*., 2018) [12] to the economic mechanisms of information-cost economizing (Williamson, 1981) [3]; (Galbraith, 1974) [8], productivity from complementary investment (Brynjolfsson & Hitt, 2000) [5]; (Brynjolfsson & McElheran, 2016) [17], and resource-based advantage (Barney, 1991) [4]; (Gupta & George, 2016) [16]. Future research may empirically test which of these mechanisms dominates at each layer of analytics, and whether logistics firms that explicitly evaluate data investment against them outperform those that adopt analytics on technical grounds alone.

This paper also concludes that the value of data science in logistics is conditional on data quality. Future work may develop measures that express the cost of poor data quality in logistics decisions, building on statistical approaches to data quality monitoring (Hazen *et al*., 2014) [10], and estimate how quality improvements change the return on predictive and prescriptive analytics.

The framework further highlights the distinctive economics of data as a nonrival good (Jones & Tonetti, 2020) [9]. Future studies may examine the governance arrangements, contracts, data platforms, and industry standards, under which logistics partners are willing to share data, and quantify the joint gains, such as reduced bullwhip amplification (Lee, Padmanabhan & Whang, 1997) [15], that sharing makes possible. The labor-market dimension also deserves empirical attention: future work may estimate how data science adoption changes the task content, employment, and wages of planners, dispatchers, and analysts, and how training programs for supply chain data scientists (Schoenherr & Speier-Pero, 2015) [18] affect the speed at which firms realize returns.

By emphasizing interdependence across analytics layers, this study highlights a shift from evaluating data science projects on technical performance toward evaluating them as sequenced economic investments embedded in an interdependent supply chain system, consistent with configurational perspectives on supply chain integration (Flynn, Huo & Zhao, 2010) [22]. Future research may investigate how firms should prioritize investment across the layers, and how they should monitor the economic return of analytics as operating conditions and data sources change (Davenport, 2006) [14].

In conclusion, this study provides a conceptual foundation for understanding data science in logistics not as a collection of analytical techniques but as a set of economic investments whose value depends on reducing information costs, on complementary organizational change, on the accumulation of proprietary data resources, on data quality, and on the adjustment of logistics labor. By making these mechanisms explicit, the proposed framework offers a platform for future research exploring empirical validation, sector-specific implementation, and theoretical refinement of the economics of data-driven logistics (Fosso Wamba *et al*., 2015) [19].

6. References

1. Mentzer JT, DeWitt W, Keebler JS, Min S, Nix NW, Smith CD, *et al*. Defining supply chain management. Journal of Business Logistics. 2001; 22(2):1-25.
2. Waller MA, Fawcett SE. Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. Journal of Business Logistics. 2013; 34(2):77-84.
3. Williamson OE. The economics of organization: The transaction cost approach. American Journal of Sociology. 1981; 87(3):548-577.
4. Barney JB. Firm resources and sustained competitive advantage. Journal of Management. 1991; 17(1):99-120.
5. Brynjolfsson E, Hitt LM. Beyond computation: Information technology, organizational transformation and business performance. Journal of Economic Perspectives. 2000; 14(4):23-48.
6. Acemoglu D, Restrepo P. Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives. 2019; 33(2):3-30.
7. Provost F, Fawcett T. Data science and its relationship to big data and data-driven decision making. Big Data. 2013; 1(1):51-59.
8. Galbraith JR. Organization design: An information processing view. Interfaces. 1974; 4(3):28-36.
9. Jones CI, Tonetti C. Nonrivalry and the economics of data. American Economic Review. 2020; 110(9):2819-2858.
10. Hazen BT, Boone CA, Ezell JD, Jones-Farmer LA. Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. International Journal of Production Economics. 2014; 154:72-80.
11. Wang G, Gunasekaran A, Ngai EWT, Papadopoulos T. Big data analytics in logistics and supply chain management: Certain investigations for research and applications. International Journal of Production Economics. 2016; 176:98-110.
12. Nguyen T, Zhou L, Spiegler V, Ieromonachou P, Lin Y. Big data analytics in supply chain management: A state-of-the-art literature review. Computers & Operations Research. 2018; 98:254-264.
13. Chen H, Chiang RHL, Storey VC. Business intelligence and analytics: From big data to big impact. MIS Quarterly. 2012; 36(4):1165-1188.
14. Davenport TH. Competing on analytics. Harvard Business Review. 2006; 84(1):98-107.
15. Lee HL, Padmanabhan V, Whang S. Information distortion in a supply chain: The bullwhip effect. Management Science. 1997; 43(4):546-558.
16. Gupta M, George JF. Toward the development of a big data analytics capability. Information & Management. 2016; 53(8):1049-1064.
17. Brynjolfsson E, McElheran K. The rapid adoption of data-driven decision-making. American Economic Review. 2016; 106(5):133-139.
18. Schoenherr T, Speier-Pero C. Data science, predictive analytics, and big data in supply chain management: Current state and future potential. Journal of Business Logistics. 2015; 36(1):120-132.
19. Fosso Wamba S, Akter S, Edwards A, Chopin G, Gnanzou D. How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. International Journal of Production Economics. 2015; 165:234-246.

20. Ben-Daya M, Hassini E, Bahroun Z. Internet of things and supply chain management: A literature review. International Journal of Production Research. 2019; 57(15-16):4719-4742.
21. Makridakis S, Spiliotis E, Assimakopoulos V. Statistical and machine learning forecasting methods: Concerns and ways forward. PLoS One. 2018; 13(3):e0194889.
22. Flynn BB, Huo B, Zhao X. The impact of supply chain integration on performance: A contingency and configuration approach. Journal of Operations Management. 2010; 28(1):58-71.
23. Whetten DA. What constitutes a theoretical contribution? Academy of Management Review. 1989; 14(4):490-495.