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Managing Changes Initiated by Industrial Big Data Technologies: A Technochange Management Model

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Abstract. With the adoption of Internet of Things and advanced data analytical technologies in manufacturing firms, the industrial sector has launched an evolutionary journey toward the 4th industrial revolution, or so called Industry 4.0. Industrial big data is a core component to realize the vision of Industry 4.0. However, the implementation and usage of industrial big data tools in manufacturing firms will not merely be a technical endeavor, but can also lead to a thorough management reform. By means of a comprehensive review of literature related to Industry 4.0, smart manufacturing, industrial big data, information systems (IS) and technochange management, this paper aims to analyze potential changes triggered by the application of industrial big data in manufacturing firms, from technological, individual and organizational perspectives. Furthermore, in order to drive these changes more effectively and eliminate potential resistance, a conceptual technochange management model was developed and proposed. Drawn upon theories reported in literature of IS technochange management, this model proposed four types of interventions that can be used to copy with changes initiated by industrial big data technologies, including human process intervention, techno-structural intervention, human resources management intervention and strategic intervention. This model will be of interests and value to practitioners and researchers concerned with business reforms triggered by Industry 4.0 in general and by industrial big data technologies in particular.

Keywords: Industry 4.0, industrial big data, technochange management, interventions, conceptual model.

1. Introduction

Since 2010s, a wide range of innovative and advanced information and communication technologies (ICTs) have emerged in our society, such as internet of things (IoT), cyber-physical-systems (CPS), advanced sensor technology, cloud computing, big data, and artificial intelligence (AI). These technologies are increasingly integrated into the manufacturing industry, and so are shifting the traditional mode of production toward smart manufacturing [1,2].

The basic concept of smart manufacturing is an intelligent production pattern, in which original physical manufacturing devices are enriched with embedded items (e.g. sensors, actuators, electronic tags, etc) that are connected to the network wirelessly [3]. In this context, a wide variety of data with respect to production process can be acquired and collected continuously in real time, and then be cleaned, correlated, stored, mined and analyzed. Moreover, the analytical results are fed back to different production devices to realize precision manufacturing and machine self-monitoring/control/maintenance. As a result, this smart manufacturing paradigm can shorten product lead-time, enable personalized, flexible and decentralized production, facilitate decision making, and maximize the utilization of resources [4].

In order to guide the national manufacturing industry to realize these benefits, the German government initially proposed a strategic plan named "Industry 4.0" at Hannover Messe in 2013. This strategy has since then been widely appreciated and adopted by other nations in Europe, and even countries across other continents (e.g. USA, China, Japan) [5]. In light of this, researchers highlighted that industrial big data plays a crucial role in any Industry 4.0 initiatives [6,7,8,9].

It is important to stress that, the implementation and usage of industrial big data will not only bring in new technological upgrades, but more importantly can also lead to essential changes and organizational reforms in manufacturing companies. Historically, changes caused by the usage of new information systems are often subjected to various internal resistance and hindrance, which can lead to major technical and business failure [10]. For the implementation of Enterprise Resource Planning (ERP) systems for example, anecdotal evidence showed that ERP project failure could result in hundreds of thousands of US dollars in economic loss, and more seriously could even trigger business bankruptcy [10]. Consequently, researchers from the information systems (IS) field highlighted that successful implementation of IT/IS projects in enterprises should be supported by adequate change management theories and methods, particularly technochange management theories, which refers to theoretical concepts and methods used to handle technology-driven organizational changes [11,12,13]. It can therefore be argued that these technochange management theories will also be important and applicable to the implementation and usage of industrial big data applications.

However, an extensive review of the current literature showed that most studies in the field of industrial big data focus mainly on technical and engineering aspects, like algorithm optimization [14,15], data modeling development [16,17], data and cyber security [18,19], or basic conceptual introduction such as concept interpretation and generalization, benefits and challenges of the usage of industrial big data [20,21]. In fact, success of industrial big data or Industry 4.0 strategy depends on the maturity of related technologies mentioned above, however, technochange management theory and approaches from an IS perspective are arguably important in the process of technical implementation and business transformation. In light of this discussion, there is currently very limited understanding and research related to changes derived from the implementation and usage of industrial big data in a manufacturing context and suitable methods to handle these changes. Therefore, this paper aims to fill this research gap through identifying potential changes caused by industrial big data implementation and investigating effective interventions that can help manufacturing organizations to cope with these emerging changes.

The results derived from this study will be important to researchers and business managers who are interested in not just the development of industrial big data and realization of Industry 4.0, but more crucially to the successful transformation for the whole manufacturing enterprise owing to the application of industrial big data. The rest of the paper is structured as follows: the next section presents the nature of industrial big data. Subsequently, an explanation of IS technochange management is given, followed by a discussion of changes triggered by industrial big data and effective interventions to cope with these changes. Finally, a theoretical technochange management model is presented with conclusions drawn.

2. Nature of industrial big data

Ever since the beginning of industrial revolution, advances in technology has resulted in severe changes and improvements in social development, particularly in the manufacturing industry. In the past, the first industrial revolution was the manufacturing of goods with machines, that is well-known as mechanization. The second industrial revolution was the realization of mass production with the assistance of electric power, followed by the digital or 3rd industrial revolution, in which electronics and IT were adopted in production [22]. At present, due to rapid development and wide application of cyber physical system (CPS), internet of things (IoT), advanced sensor technology, communication technology, computer and science technology, these technologies are increasingly adopted and deployed in manufacturing field. Therefore, manufacturing industry is experiencing a major leap forward, which can be considered as the 4th industrial revolution or Industry 4.0 [23].

To be specific, for instance, under the help of advanced sensor technology and communication technology, various types of sensors and actuators are installed in different devices and production lines, tremendous amounts of industrial data particularly real-time machine data (e.g. switching time, machine logs, real-time alarm, temperature) and product data (e.g. quality assurance, raw material codes) is collected, transferred and stored in cloud server [24]. Moreover, those collected industrial data are scrubbed, screened and analyzed by the aid of cloud computing and relative data process technology like machine learning, deep learning approaches (e.g. navie bayes, convolution neural network, k-means clustering algorithm) [25]. Furthermore, data analysis results will be fed back to the production process in order to realize intelligent control, smart deployment, predictive diagnosis and precise management over raw materials, production device, detection device and even the whole manufacturing process, which is considered as the vision of Industry 4.0. Under this circumstance, there is no doubt that industrial big data plays and will continue to play an increasingly important role toward realizing Industry 4.0.

When many authors (e.g. [24,25]) emphasized on the production sets of industrial big data, other researchers indicated that industrial big data actually contains a much wider coverage that goes beyond the boundary of production units. In particular, Yan et al argued that industrial big data refers to all types of data generated from the whole product life cycle, covering sales, product design and development, production, procurement, supply chain, stock control, delivery, and after-sales services [26]. Lee et al pointed out that industrial big data also includes Internet data related to market trends, customer behavior, and competitor performance [20]. A further analysis of the literature [14,16,24,27] suggested that, these various categories of industrial big data can be generated and collected from three types of sources, including:

- Management information systems. A large amount of industrial big data is derived from internal management information systems like ERPs, supply chain management (SCM) systems, customer relationship management (CRM) systems, manufacturing execution systems (MES), product lifecycle management (PLM) systems, etc. For example, there are lots of product design data in PLM, such as product drawings, CAD, CAE, and bill of materials (BOM) of product. Besides, data related to operation and customer like staff behavior, KPIs, stock records can all be stored in management information systems.

- Shop-floor machines. The complex component of industrial big data comes from shop-floor machines. The machine data is mainly acquired and collected from various sensors that are integrated in production lines, such as data of machine temperature, rotating speed, fault detection, product quality, availability and repair rate. In reality, shop-floor machine data is regarded having three characteristics, that is, real-time, dynamism and uncertainty. At present, large amounts of machines are working in factory synchronously. Under this circumstance, shop-floor machine data has the fastest growth and vital significance in maintaining the machine health.
- External environment. External data is the third category of industrial big data from the perspective of data source, and refers to data that is not included in the enterprise in-house systems. According to the study conducted by McKinsey, nearly 90 percent external data is generated from internet, including internet market data (e.g. news, blog, etc), raw material data, data related to competitor's product, etc [28].

Interestingly, compared with the popular word 'big data' that discussed widely by both academic and the media, industrial big data possesses partial overlapped characteristics (e.g. volume, variety and velocity) as big data, but it still has its unique features, for instance, sequence, strong-relevance, accuracy and closed-loop [26], as detailed in figure 1.

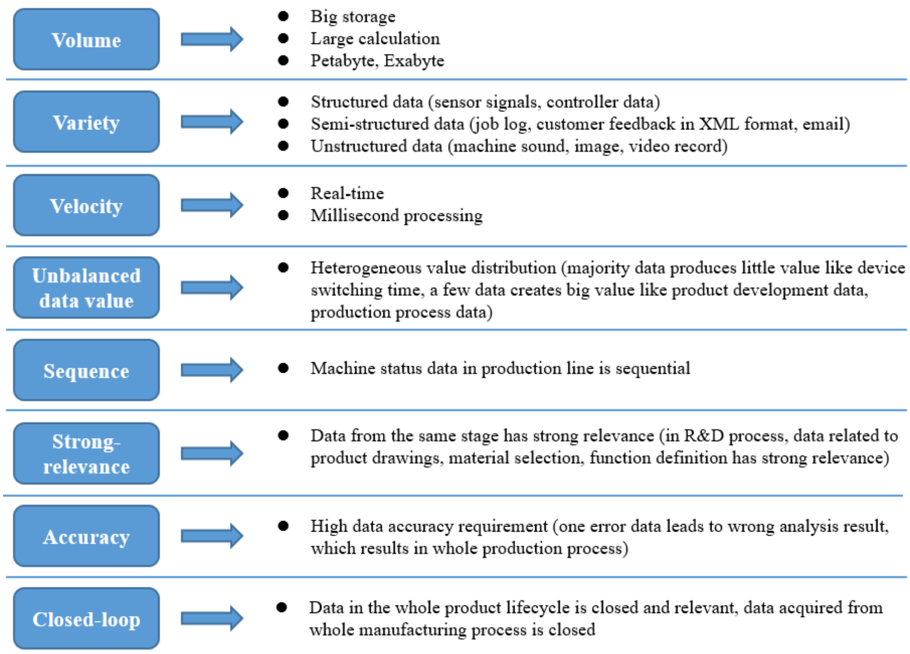

Fig.1. Characteristics of industrial big data

3. IS technochange management

The concept of technochange was firstly coined by Markus, who defined that "*Using IT in ways that can trigger major organizational changes creates high-risk, potentially high-reward situations, that called technochange*" [12]. A technochange management initiative is not merely an IT-based project or an organizational change program, but the combination of both (Table 1 summarizes their differences in detail). Generally, a pure IT project usually has a strong technological focus on improving technical performance (e.g. processing speed, reliability, functionality) of the system, but may pay less attention to organizational, management and human-related problems. Meanwhile, a pure organizational change program pays close attention to people and business issues, but may have nothing to do with the adoption of new technologies [12,29]. In contrast, a technochange management program is characterized by completeness, effectiveness and feasibility, and combines technical solutions with considerations regarding organizational structure, processes, business culture, and human needs [30]. In short, a technochange management program is an integrated initiative that manages organizational changes in conjunction with the adoption and usage of information technologies.

Table.1 Technochange vs IT project and organizational change program [12]

	IT project	**Organizational change program**	**Technochange management**
Solutions	New information technology adopted	Changes of people, structure, culture, policy	Changes due to information technology implementation
Approaches	Normally led by IT manager	Normally led by CEO and HR manager	All departments of enterprise cooperate comprehensively, typically led by CEO and other branch managers collaborate together
IT expert	Very important, manage the quality of new information technology	Insignificant	Balanced, IT expert should work with other department's managers to redesign work processes and related organizational components
Target	Technology performance (e.g. response speed, security)	Organizational performance (e.g. flat structure, a good corporate culture)	Reasonable organizational changes in conjunction with implementation of information technology (e.g. organizational structure change, job redesign, new reward system)

Under the concept of technochange management, the term "intervention" should be highlighted. An intervention can be defined as a set of sequenced and planned activities that can systematically improve organization deficiencies and members' attitudes, values, skills and interpersonal relationships, and so make the organization and its people adapt to new changes more effectively [29]. With this definition in mind, many research studies (e.g. [30,31]) demonstrated that changes initiated by new information technologies are complicated, and so the corresponding interventions used to cope with these changes will vary according to the actual project contexts and organizational needs. For example, the adoption of ERP system emphasizes integrity and consistency of the enterprise as a whole rather than independent work among different departments [32]. In this case, past routine work and jobs will be adjusted and replaced, which needs more communication and information sharing among a variety of units within an organization and co-ordination of personnel to make sure successful application of ERP. The intervention of business process reengineering is thus often applied in ERP projects to facilitate changes related to process redesign [33]. On the other hand, employees need to use the new ERP system on a daily basis to improve their work performance. A comprehensive training program should thus be designed and used as an intervention to equip different types of users with the needed technical skills [31].

When there is a rich number of literature discussing technochange management and related interventions in an IS context, this discussion has currently not been much extended to the application of industrial big data technologies. As an important component to realize Industry 4.0, industrial big data will undoubtedly trigger essential changes and even reforms in organizations. The relevance of existing interventions to deal with these changes will also need to be further explored and considered. The next section attempts to provide further insights, derived from the literature review as well as our previous research work and practical experiences, to address these knowledge gaps.

4. Technochange management for industrial big data applications

4.1 Potential changes initiated by industrial big data

The application of industrial big data will inevitably trigger technological upgrades and changes in user companies. These technical changes will have substantial influences on individual's daily work, and eventually lead to profound transformation across the whole organization. This section provides a detailed profile of potential changes caused by industrial big data, respectively in technological, individual and organizational levels.

4.1.1 Technological changes

As discussed in section 2, industrial big data is huge in terms of volume and it has different attributes, sources and structures, which thus raise new challenges to traditional data processing and analyzing infrastructures. In order to cope, manufacturing firms need to use more updated and efficient data storage and analytical technologies to maximize the utilization of industrial big data, as outlined in Figure 2. In particular, cloud computing technologies (such as Google File System or GFS, MapReduce) and big data processing platforms (like Hadoop) are widely perceived as driving forces to boost technological reforms, as well as to enable smart automation and predictive management, in the Industry 4.0 environment [16].

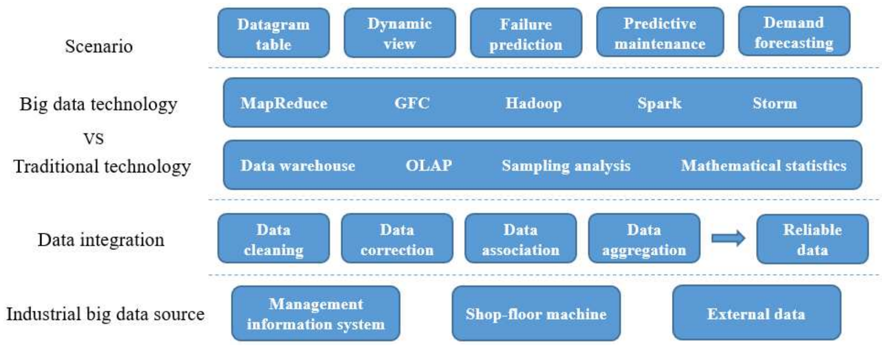

Fig.2. Basic components of industrial big data process

4.1.2 Individual changes

Hackman & Oldham proposed a job characteristics model that has impacts on employees' work satisfaction and motivation [34]. This model comprises of five core elements, namely:

- Skill variety: jobs involving a variety of skills and activities can better motivate and attract employees;
- Task identity: jobs with clearly-defined tasks and goals are more likely to lead to positive feelings of achievement;
- Task significance: jobs with clear meaning, significance and impact can make employees feel more satisfied;
- Autonomy: employees generally enjoy the level of freedom given to them to accomplish their tasks;
- Job feedback: employees want to be told when they are doing well and when they are not.

It can be argued that the intensive application of industry big data will result in changes of individual employee in all of these five elements:

- **Changes in skill variety:** many traditional jobs (e.g. product quality assurance, stock control) will be replaced by intelligent machines with support of analytical results derived from industrial big data. Employees are also required to develop and learn new skill sets, e.g. certain degree of data modelling and data analysis capabilities that can help them make better decision in work.

- **Changes in task identity & significance:** Industrial big data runs through the whole product lifecycle and connect all units together, and so making the enterprise more integrative. Individual tasks and roles will need to be refined and precisely defined. In this context, people and machines' work will coordinate and interrelate with each other. Tasks done by individuals will also have greater importance and impact organization-wide.
- **Changes in autonomy:** Analytical results and predictions derived from industrial big data tools can empower employees and allow them to have more autonomy in making work plans and decisions.
- **Changes in job feedback:** Industrial big data enables managers and front-line staff to understand better their job performance in a timely and clear manner. Meanwhile, according to the needs of enterprise, suggestions are provided based on industrial big data analysis for individuals to improve their work efficiency.

4.1.3 Organizational changes

In the environment of Industry 4.0, technological and individual change will lead to profound organizational reform throughout the enterprise eventually. Researchers (e.g. [30,31]) disclosed and emphasized that organizational change is a long-term process and cannot be accomplished in one go. According to the organizational diagnosis model proposed by Cummings and Worley [35], organizational changes can occur in four essential aspects, including organizational structure, management process, human resource systems and business strategy. The application of industrial big data can have far-reaching impacts on all of these organizational aspects:

- **Changes in organizational structure:** The application of industrial big data tools and intelligent automatic systems will reduce the demand of team leaders in shop floor and even middle managers in the tactical level. This will enable a flatter, more decentralized, and networked nature of organizational structure. In addition, new functional units and job positions (e.g. big data center, data analyst, data scientist, etc) will also be set up to support the organization in the new technological environment.
- **Management process:** In traditional management process, managers can only adopt a reactive approach to deal with business issues when they occur. With support of predictive analysis done by industrial big data applications, managers

can now become more proactive and take early actions to deal with production and business problems before they even happen.

- **Human resource systems:** Human resource systems consist of mechanisms for employing, appraising and rewarding members in the organization. Organizations should hire more staffs who has the ability to perform well in the environment of industry 4.0. Moreover, organization should provide some training course for staffs to develop data-driven awareness and data analysis skills.
- **Strategy:** Business strategy will be formulated driven by data analytical results rather than top managers' experience and intuition. As a result, resources (human, finance, technology) can be assigned and used more scientifically and efficiently.

4.2 Interventions applied in the usage of industrial big data

It was clearly demonstrated from the above discussion that, in order to realize the full potential of industrial big data applications, individuals need to change not only their original ways of working but also their roles, behaviors and attitudes. Moreover, the organization as a whole will need to undergo severe reform in order to suit the new technological environment. Successful advancement of these individual and organizational changes can accelerate technological changes, on the contrary, it can create strong internal resistance and even lead to technical failure during the adoption of industrial big data technologies [35].

In order to copy with the changes triggered by the application of industrial big data, four types of interventions commonly adopted in IS projects can be considered and used during the adoption of industrial big data tools, namely human process interventions, technostructural interventions, human resource management interventions, and strategic interventions.

4.2.1 Human process interventions

Human process interventions derive mainly from the disciplines of psychology and it refers to actions and programs taken to improve interpersonal relations [36]. In an organization, the major aim of human process interventions is to strengthen the relationships and cooperation among employees in different departments and across all levels [36]. The basic approaches of human process interventions include team building, process consultation, organization confrontation meeting and interpersonal communication training [37]. When an organization implements an industrial big data application, it requires all units to work together along the entire product life cycle. Human process interventions can thus help to break down departmental boundaries and barriers and so facilitate effective usage of industrial big data tools organization-wide.

4.2.2 Technostructural interventions

Technostructural interventions are concerned with both new technologies and structure of the organization [38]. The main purpose of technostructural intervention is to change and improve the organizational structure according to the needs of the changing technology environment. Typical technostructural interventions include structural redesign, downsizing, business process reengineering, high-involvement, job enrichment, etc [38]. In particular, structural redesign and business process reengineering are two typical and important interventions applied in IS projects in general and industrial big data projects in particular.

4.2.3 Human resource management interventions

Human resource management interventions are associated with issues like hiring, appraising, rewarding, developing and supporting employees in organizations [35]. With the implementation of industrial big data tools, traditional labor-intensive production mode will be replaced by smart manufacturing mode gradually. This will put forward a demand for new personal skills and new knowledge of employees. Human resource management interventions, such as goal re-setting, reward system redesign, coaching and mentoring can encourage employees to develop new skills, enable people with the right quality to be selected, and ensure staff with good performance to be rewarded in the new technological environment.

4.2.4 Strategic interventions

Strategic interventions are associated with the changing of business goals and transforming the organization to keep pace with internal and external changing environments [39]. Specifically, strategic interventions include organization redesign, integrated strategic change, culture redesign, dynamic strategy making, etc [40]. As discussed earlier, industrial big data applications will have long-term and profound impacts on enterprise strategy making. Therefore, organization needs to have a long-term plan based on their business strategy rather than concerning about short-term needs. Strategic interventions (especially culture redesign and dynamic strategy making) can be applied by manufacturing companies to ensure they have a healthy organizational culture and strategic decision making environment to deploy and use industrial big data applications effectively in the long-term plan.

4.3 Technochange management model

Based on analysis and discussions made above, a technochange management model for industrial big data is proposed and developed, as shown in Figure 3.

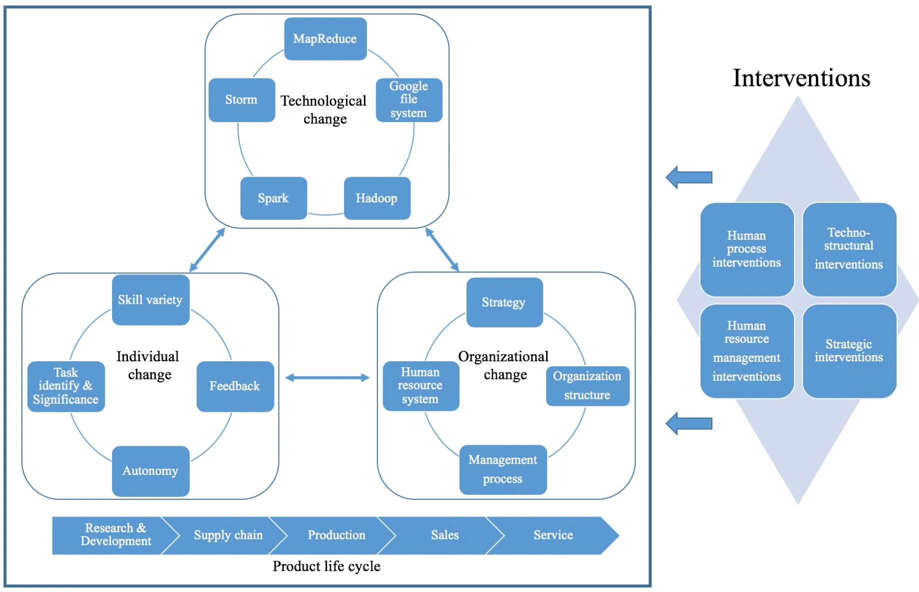

Fig.3. Conceptual technochange management model for industrial big data

As shown in the model, for any manufacturing firms, technology, individual and organization are closely interrelated with each other. As such, technological changes can always lead to essential changes in individual and organizational levels. Moreover, individual and organizational changes can in turn either facilitate or hinder technological changes in enterprises. In order to cope with potential resistance to these changes, the four types of technochange management techniques and interventions will need to be selected and used as relevant in industrial big data projects.

5 Conclusion

For nearly two decades, the concept of technochange management has attracted the attention of both IS researchers and practitioners. It is arguable that effective management of individual and organizational changes can substantially increase the possibility of IS success. It is deemed that this argument can be highly applicable and suitable to the context of industry 4.0 in general and the usage of industrial big data tools in particular, but it is hard to retrieve current literature to support and explore this phenomenon. We therefore try to explore in this paper different types of potential changes initiated by the adoption of industrial big data technologies, as well as to demonstrate how a variety of technochange techniques and interventions can be useful in this context. A conceptual technochange management model is then developed and proposed to sum up these insights. More importantly, this conceptual model can serve as a theoretical foundation to guide future research on this topic, and can also be used as the basis for high-level change management planning in practice. We admit that technochange management in the context of industrial big data projects is a very complicated topic, and that the proposed model is relatively simple. However, we attempt to use this paper to bridge the concepts of technochange management, industry 4.0 and industrial big data, and hope more in-depth research can be done on this increasingly important topic in the near future.

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