Smart and efficient: Learning curves in manual and human-robot order picking systems

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Abstract: Order picking has been identified as the most labour-intensive, as well as costly activity within warehouse logistics and is experiencing significant changes due to new technologies in the forms of artificial intelligence (AI) and automation. One fundamental question concerns the employees learning progress in human-robot picking systems compared to existing manual technologies. Therefore, this paper presents an empirical analysis of learning curves in manual pick-by-voice (n=30 pickers) and semi-automated (n=20 pickers) order picking. Aspiring to measure the individual learning progress without a priori assumptions, this publication is the first to apply Data Envelopment Analysis and examine order pickers learning curves in real application scenarios. The findings indicate that automating human work accelerates the individual learning progress in human-robot picking systems.

Keywords: automation, efficiency, human factors, learning, order picking, DEA.

1. INTRODUCTION

Recent advances in the areas of computer science, engineering, robotics, and information science have spawned remarkable digital progress in the fields of production as well as transport and logistics. In warehouse logistics, robots are already used to handle routine picking and sorting tasks. Although it is possible to automate order picking processes through new technologies, human worker's activities are still required (Lee, J. Ae, Chang, and Choe 2017). Previous research has predominantly focused on cost-efficiency goals, and little attention has been given to human factors (Grosse, E. H., Glock, and Neumann 2015). From a human factors perspective, learning curves are detailed examined in the field of order picking, mostly in laboratory or experimental settings (Zhang et al. 2019; Winkelhaus et al. 2018; Stinson and Wehking 2016; Grosse, E. H. and Glock 2013; Glock et al. 2019). Concurrently, the applied traditional learning curve theories are parametric functions requiring a priori knowledge, which is critical for new technology evaluation. Therefore, this contribution closes two research gaps in learning curve theory: (1) It is the first empirical investigation of learning curves in real application settings within order picking while focusing on new technology implementations like digital pick-by-voice or pick-by-light systems and (2) it is the first empirical measurement of learning curves without a priori assumptions.

Due to the lack of prior research on automating human workforce and its impact on the individual learning progresses, this publication aspires to answer the following research questions (RQ): RQ_1 *What is a suitable method to measure learning curves in order picking without requiring a priori knowledge?* and RQ_2 *How do learning curves in human-robot order picking systems differ from learning curves in manual pick-by-voice order picking systems?*

Aspiring to answer these RQ, the contribution is structured as follows: Firstly, we review the literature relating to traditional models requiring a priori knowledge and empirical research on learning curves in order picking. Secondly, we present the methodology by introducing and justifying the application of Data Envelopment Analysis (DEA). Then we provide an analysis of the empirical results, separated into the two case studies examining the pick-by-voice picking system on the one hand and the semi-automated picking system on the other hand. After discussing the results of our empirical findings, we make a conclusion.

2. LITERATURE REVIEW

2.1 Traditional models requiring a priori knowledge

A contribution of Wright (1936) entitled "Factors affecting the cost of airplanes" was the first examination of the learning phenomenon in the context of industrial production. Since then, there have been many publications discussing methodological enhancements in learning curve theory (Towill, D. R. 1985; de Jong 1957; Jaber and El Saadany 2011; Carlson 1973) or applying learning curve models to empirical cases in operations management (Terwiesch and E. Bohn 2001; Grosse, E. H. and Glock 2013; Gunawan 2009; Nembhard and Osothsilp 2001) and technology implementation management (Plaza, Ngwenyama, and Rohlf 2010). Literature reviews examining learning curves (Stroieke, Fogliatto, and Anzanello 2013; Anzanello and

Fogliatto 2011; Glock et al. 2019; Grosse, E. H., Glock, and Müller 2015; Yelle 1979), categorize (1) the object of research to performance improvements of individuals, groups, or organizations (Grosse, E. H., Glock, and Müller 2015) and (2) learning curve models into log-linear models, exponential models, hyperbolic models, learning models for scheduling, and learning and forgetting models (Glock et al. 2019). When looking at the mathematical formulation of traditional parametric learning curve theories, it is noticeable that a priori assumptions have to be made. The Wright learning curve is defined as follows:

$$F = N^x \quad (1)$$

In (1), F is the cumulative average time to produce a unit, N is the time to produce the first unit, and x is the learning exponent calculated through x = log F/ log N. This learning exponent requires an a priori specification of the learning curve gradient (Wright 1936, p. 124). Further enhancements of learning curve theory include a priori prescribed target time (Baloff 1970; Baloff 1971), number of repetitions required to reach this time (Jaber and Bonney 2003), or the factor of incompressibility (de Jong 1957, pp. 53-54):

$$T_s = T_1\left(M + \frac{1-M}{s^m}\right) \quad (2)$$

In (2), T_s is the time required for the s^{th} cycle of the batch, T_1 is the time required for the first cycle of the batch, M is the factor of incompressibility (M=0 manual, M=1 automated), s is the number of cycles and m is the is the exponent of the reduction ($0<m< 1$). Other theories aspire to split the task into several elements (Globerson 1980), or differentiate between cognitive and physical learning (Dar-El, Ayas, and Gilad 1995), whereby the mathematical formulation of Dar-El, Ayas, and Gilad requires the a priori formulation of cognitive and physical learning exponents. To summarize, existing theories are based on parametric mathematical functions that rely on a priori assumptions about functional relationships. From a business practice perspective, empirical investigations in operations management and logistics often lack this knowledge when it comes to the implementation of new technologies. Furthermore, they neglect the individual performance capability of humans by assuming equality. As order picking is a labor-intensive task, the physical condition plays an important role that falsifies results when it is not given attention to.

2.2 Empirical research on learning curves in order picking

Besides empirical replications of Wrights model (Nembhard and Osothsilp 2001; Gunawan 2009), learning curve theories have been applied to production (Argote and Epple 1990; Chung 2001; Pramongkit, Shawyun, and Sirinaovakul 2000), services (Foster 1992; Woods et al. 1992) and logistics (Chen, M. Kuen, Wang, W. Yinghan, and Hung 2014; Jaber and El Saadany 2011). Publications to warehouse logistics are broadly diversified concerning the object and the context of research but are monotonous when looking at the applied research design. Zhan et al. examine the order pickers' learning effects on the order fulfillment process in an online-to-offline community supermarket depending on scheduling algorithms in an experimental setting (Zhang et al. 2019). A similar research design is used by Winkelhaus et al., investigating the effects of human fatigue on learning in order picking in an explorative experiment (Winkelhaus et al. 2018), by Stinson, with an experimental analysis of manual order picking processes in a learning warehouse (Stinson and Wehking 2016), or by Grosse and Glock, with an experimental investigation of learning effects in order picking systems at a manufacturer of household products (Grosse, E. H. and Glock 2013). Another experimental setting combining a training situation with a head-mounted device for displaying virtual reality content is presented by Elbert, Knigge, and Sarnow (2018). Further contributions related to learning curves in order picking develop analytical models, simulations, or theoretical framework, aiming to describe the process of learning in order picking (Grosse, E. H. and Glock 2015; Grosse, E. H., Glock, and Jaber 2013; Shafer, Nembhard, and Uzumeri 2001).

In conclusion, empirical investigations based on real live data are hardly addressed in practical level theory development. This can have several reasons: (a) logistics companies produce real live data through their daily business operations, but are not willing to share it with scholars, (b) scholars cannot use the real live data possibly provided by companies, (c) there is no a priori knowledge in real-life cases which can be applied to the existing traditional models of learning curves or (d) the amount and the composition of a priori knowledge that is required for an application of conventional learning curve models to real-life settings, is too complex.

3. METHODOLOGY

3.1 Efficiency measurement without a priori knowledge

To calculate the efficiency as a single-item measurand of the construct learning progress, this paper proposed a DEA model with an input-oriented ratio form under constant returns to scale (CRS). DEA is a non-parametric optimization method of mathematical programming for measuring the relative efficiency of decision-making units (DMUs) that have multiple inputs and outputs. A basic model was introduced by Charnes et al. (Charnes, Cooper, & Rhodes, 1978, pp. 429-444) and is based on Koopmans activity analysis concept (Koopmans, 1951) together with the publications of Debreu and Farrell dealing with radial efficiency measurement (Debreu, 1951; Farrell, 1957). Further advantages beyond multiple inputs and outputs included are the facts that DEA is solely based on empirical data without the need for a priori existing production function and the fact that there is no need to weight factors, as this is done endogenously by the mathematics optimization model. The production process or throughput is seen as a black box. The basic mathematical notation is as follows (Wilken, 2007, p. 35).

$$\text{eff DMU}_0 = \frac{\textit{virtual outputs of } DMU_0}{\textit{virtual inputs of } DMU_0} = \frac{\sum_{j=1}^{s} u_{0,j}\; y_{0,j}}{\sum_{i=1}^{m} v_{0,i}\; x_{0,i}} \quad (3)$$

In (3), eff is the abbreviation for efficiency, DMU_0 is the DMU with index 0 as an exemplary decision unit, s is the number of outputs to each DMU, m is the number of inputs to each DMU, $u_{0.j}$ is the weight assigned to the output, $v_{0.i}$ is the weight assigned to the input, $y_{0.i}$ is the amount of the j output produced by DMU_0 and $x_{o.i}$ is the amount of the i input consumed by DMU_0.

Four characteristics of new technology implementation justify the application of DEA as a key research method: (1) The impact of new technologies is not predictable and not yet examined from an efficiency-based point of view. Therefore, there is no a priori knowledge about functional relationships of new technologies towards humans. (2) Because the new technologies are influencing the human workforce, the theory of work systems is applied as a theoretical framework within the case analyses. As the achievement of work objectives requires input and produces output, a method that enables the integration of several in- and output factors along with the possibility of factor enhancement is required. (3) Without the existence of a benchmark value for the level of efficiency in new technology scenarios, the analysis has to compare the performance of the empirical observations with each other. (4) As it is unclear if new technologies spawn an immediate or gradual efficiency development, the progress of efficiency in retail logistic is illustrated with an empirical curve progression. Therefore, the results of the analysis have to be comparable among several periods. As DEA does not require a priori information (requirement 1), does consider multiple measures (requirement 2) (Cooper, Seiford, and Zhu, J. 2011), does compare solely the empirical observation among each other (requirement 3) (Charnes, Cooper, and Rhodes 1978) and the results are comparable when factors are constant (requirement 4) (Cooper, Seiford, and Tone 2007; Cooper, Seiford, and Zhu, J. 2011), it is the method of choice. This elaboration answers RQ_1.

3.2 Definition of input and output variables for DEA model

The elaboration of the DEA model begins with the selection of appropriate input and output measures, whereby two requirements have to be fulfilled to provide generalizable and practically relevant results: (1) the model has to be able to measure the efficiency of pick-by-voice and human-robot operations. Therefore, the integration of specific factors, e.g., the response time of speech recognition, cannot be applied. (2) Although the model has to reach a cross-technical perspective, recent and practically substantial factors have to be involved, e.g., if time minimization through route optimization is essential, order picking time has to be included in the input or output measures. When looking at the literature, there are hardly publications applying DEA to order picking. Johnson and McGinnis (2010) examine order picking as a business unit and from an organizational perspective. Therein, labor, space, equipment, and inventory are used as inputs transformed by the warehouse. Outputs are piece lines, case lines, pallet lines, returns, value-added services, storage, and accumulation. As this publication aims to get insight into the human-machine interaction on an individual level, the approach cannot be applied. Chen, C.-M. et al. (2010) create a framework combining data envelopment analysis, ranking and selection, and multiple comparisons. Therefore, inputs and outputs are not defined for a CCR or BBC model, but order size, setup time, picking time, sorting time, and travel speed are included in the analysis. The following input measures are applied to the operational efficiency model:

y_1, total picking time: As order picking is a laborious and time-intensive warehouse process, the sum of total picking hours represents the human resources invested in the picking process. Focusing exclusively on the core process picking, this measurand indicates how well human resources utilize their work equipment. For the DEA model, the period between (a) receiving general order data from picking system and (b) finishing batch through transfer to next workstation, is taken into account. The data was extracted from the warehouse management system.

y_2, total operational expenses: These expenses occur when employing order pickers and include basic salary and employee-specific bonuses as gross salary, aiming to exclude individual wage effects, e.g., individual tax class. The data was extracted from anonymous payroll journals.

On the output side, the individual performance of order pickers can be measured by two different indicators.

x_1, total SKUs picked: Because the most important output of the order picking process is physically compiled orders, the units picked by the individual order picker is used as an output. As the total amount of picked units correlates with the first input, total picking time of order picker, the SKU in the sense of targeted storage locations are used.

x_2, revenue earned for logistics service: As the fees for logistics services paid by the sales unit of the retailing company are the only incoming revenue stream for the logistics unit, it is considered as an output. It is calculated per transport unit and depends on the number of picks, the total weight of the SKUs, as well as the distance between the warehouse and the individual shop.

As scientists and practitioners seek to minimize picking time and costs for order picking, this paper proposed a DEA model with an input-oriented ratio form. As DMUs, the smallest logistical unit of warehouse logistics, the order pickers, are used. On the one hand, this enables the examination on an individual level, and, on the other hand, it is a novel approach when looking at existing efficiency measurements in warehouse logistics as described above.

4. EMPIRICAL RESULTS AND ANALYSIS

4.1 Manual pick-by-voice picking system

Two case analyses C_1 and C_2 are conducted in the field of warehouse logistics of a large German full-range food retailing company. The picking sector is responsible for a complete and on-time order compiling based on the demand of the grocery shops. Focusing the daily business of an order picker and the physical material flows, the work process can be divided in the following steps: (1) get empty transportation aids, (2) receive general order data from picking system, (3) receive storage locations for picking, (4) move to storage locations, (5) pick n SKU from storage location, (6) put on transportation aids, (7) verify pick by scanning verification code, (8) repeat (4)-(7) till order is finished, (9) receive location of printer for label and (10) bond label on finished order. In order to investigate the area with maximum interaction between human and digital work object, the work system order picking is examined by including steps (2) to (9). C_1 examines the incorporation of five order pickers during seven weeks, on a half week basis, e.g., the first half of week one W1H1 and the second half of week 1 W1H2, whereby their performance is compared to a n=10 control group in order to analyze the learning curve from an efficiency-based point of view. For this purpose, the data of approximately 278,000 picks during 1,630 hours of picking time was analyzed. C_1 uses input and output factors described in the previous chapter and applies an input-oriented BCC model. VRS is used due to the following reasons: (1) The results of the CCR and the BBC models are not similar, (2) it is assumed that the MPSS, in C_1 and C_2 the individual performance capability of the order pickers, is not equal (Banker, 1984).

Figure 1 illustrates the results. Therein, the incorporation group shows an increasing level of efficiency from t_{W2} to t_{W4} with varying strength of improvement from day to day. Whereby the first weeks have an extremely low improvement of average efficiency for the incorporation group, the overall development, measured by the mean value from t_{W2} to t_{W4}, is significant (eff_{W3} = 0.46; eff_{W5} = 0.61; eff_{W7} = 0.72, eff_{W9} = 0.88).

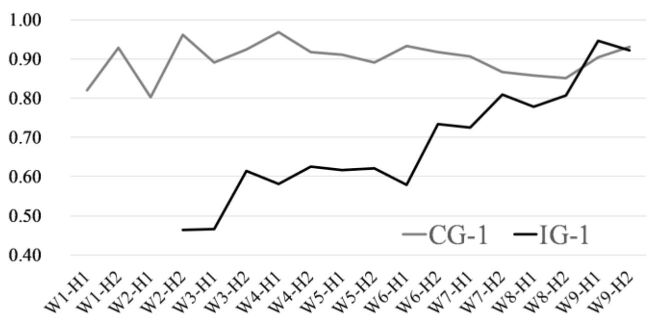

Fig. 1. Efficiency progression for order pickers in C_1

The efficiency progression of the control group is stable, within 0.80 and 0.95, which can be explained by a high number of missing articles that caused inefficient subsequent order picks. Due to the increased efficiency level of the incorporation group in t_{W6} to t_{W9}, the management decided to reduce the control group from $n_{CG,1}$ = 10 to $n_{CG,1}$ = 5 to avoid space problems in the picking area. The random selection of a control group in t_{W7} caused volatile efficiency values. C_1 shows that DEA is a suitable evaluation method for learning curves of order pickers and an appropriate control method for staff assignment within incorporation scenarios.

C_2 follows the general logic of C_1 but applies detailed briefing including operating principles and an in-depth explanation of the work process in order to provide insights, whether the briefing method for order pickers changes the learning progress.

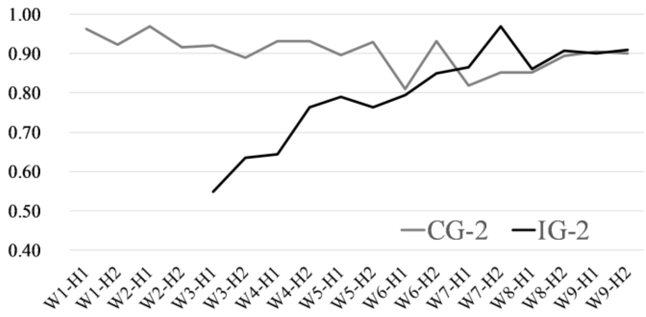

Fig. 2. Efficiency progression for order pickers in C_2

C_2 examined data of approximately 226,000 picks during 1,370 hours of picking time. The results confirm the findings of C_1 with an increasing level of efficiency for the incorporation group from t_{W3} to t_{W5} with varying strength of improvement from day to day. It can also be derived that a period of approximately 7 to 9 weeks is a suitable value for the incorporation of order pickers until they reach the level of the experienced workforce within a pick-by-voice system. C_2 validates the perception that DEA is a suitable evaluation method for learning curves in warehouse logistics of food retailing. The detailed briefing in C_2 had an effect on the learning progression of order pickers compared to their performance in C_1.

4.2 Semi-automated picking system

The third case analysis C_3 is also conducted in the field of warehouse logistics of a large German full-range food retailing company but within a semi-automated picking system. Within a person-to-good logic, the order picker is standing in a cabin and shifted by storage and retrieval machine from one picking position to the next. Furthermore, the system uses projectors to display where to put down stock keeping units (SKU) on the transportation aid and therefore augments reality. Focusing the daily business of an order picker and the physical material flows, the work process can be divided in the following steps: (1) automatic supply of empty transportation aids, (2) receive general order data from picking system, (3) automatic move to storage locations, (4) pick n SKU from storage location, (5) put on displayed position, (6) confirm by holding security buttons, (7) repeat (4)-(6) till order is finished and (8) bond label on finished order. In order to investigate the area with maximum interaction between human and digital work object, the work system order picking is examined by including steps (2) to (7). C_3 examines the incorporation of ten order pickers during seven weeks, on a half week basis, e.g., the first half of week one W1H1 and the second half of week 1 W1H2, whereby their performance is compared to a n=10 control group in order to analyze the learning curve from an efficiency-based point of view. For this purpose, the data of approximately 1,000,000 picks during 3,630 hours of picking time was analyzed. C_1 uses input and output factors described in the previous chapter and applies an input-oriented BCC model as in C_1 and C_2. Figure 3 illustrates the results.

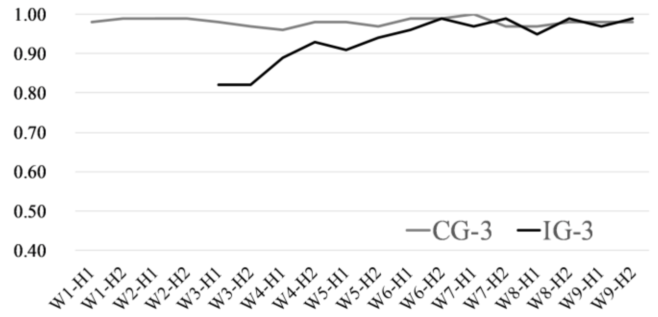

Fig. 3. Efficiency progression for order pickers in C_3

The efficiency progression of the control group is stable, within 0.96 and 1.00. The incorporation group shows an increasing level of efficiency from t_{W3} to t_{W5} with varying strength of improvement. A high improvement of efficiency can already be observed within the first weeks and the overall development, measured by the mean value from t_{W3} to t_{W6}, is significant. It can be observed that starting with the 6th week the incorporation group is as efficient as the control group.

5. DISCUSSION AND CONCLUSION

When looking at the learning curves of the incorporation groups in isolation, the starting points are significantly different. While explaining the system to order pickers in C_2 leads to an efficiency gain at the beginning, automating human work boots the starting point. Moreover, in C_3, the incorporation groups reach the efficiency level of the control group after 6 weeks, while in the manual order picking systems, the efficiency level of the control group is reached after 9 weeks. Automating human work accelerates the individual learning progression of order pickers by (1) making them more efficient at the beginning of the incorporation phase compared to manual picking systems and by (2) enabling steeper learning curves to reach the level of experienced pickers earlier.

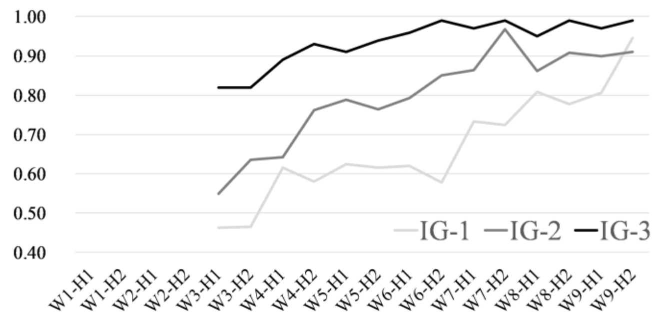

Fig. 4. Comparison of incorporation group in C_1, C_2 and C_3

Comparing the results to a previous study of Stinson (2014), who investigated learning curves of temporary workers that took six weeks until they reached a good performance level, this study confirmes the approximate incorporation time and the learning progression during this timeframe. Opposing the learning progression of order pickers to other DEA studies of blue-collar workers, Loske and Klumpp (2018) showed a similar learning progression for truck drivers that learn to utilize handheld scanners. From a theoretical viewpoint, the publication evidenced that DEA is suitable when it comes to the efficiency impact of new technology implementations, as parametric functions requiring a priori knowledge are not requisite. For logistics managers in retail logistics, automating human work in warehouses is often associated with semi-automated or fully automated order picking. In the context of semi-automated human-robot picking systems, business cases are often based on the reduction in labour costs and an increase in efficiency as well as the packing quality. Through this contribution, managers can now rethink the consequences of personal costs when automating human work, as shortened learning cycles will open the possibility of relying more on temporary employment forms in high season periods. While enlarging the proportion of non-experienced workforce in manual order picking systems entails inefficient periods with quality losses, the additional acquisition will have considerably lower hurdles when automating human work. With the help of the progress in knowledge developed through this publication, managers can now reduce personnel costs, by keeping the regular crew as little as possible and increasing picking capacity with additional personnel in peak times, as the management caused fluctuation effect is less expensive through shorter learning curves.

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