

A variability taxonomy to support automation decision-making for manufacturing processes

Yee Mey Goh, Simon Micheler, Angel Sanchez-Salas, Keith Case, Daniel Bumblauskas & Radmehr Monfared

To cite this article: Yee Mey Goh, Simon Micheler, Angel Sanchez-Salas, Keith Case, Daniel Bumblauskas & Radmehr Monfared (2020) A variability taxonomy to support automation decision-making for manufacturing processes, *Production Planning & Control*, 31:5, 383-399, DOI: [10.1080/09537287.2019.1639840](https://doi.org/10.1080/09537287.2019.1639840)

To link to this article: <https://doi.org/10.1080/09537287.2019.1639840>



© 2019 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.



Published online: 31 Jul 2019.



Submit your article to this journal [↗](#)



Article views: 536



View related articles [↗](#)



View Crossmark data [↗](#)

A variability taxonomy to support automation decision-making for manufacturing processes

Yee Mey Goh^a, Simon Micheler^a, Angel Sanchez-Salas^b, Keith Case^a, Daniel Bumblauskas^c and Radmehr Monfared^a

^aWolfson School of Mechanical, Electrical and Manufacturing Engineering, Loughborough University, Loughborough, United Kingdom;

^bDepartment of Mechanical and Industrial Engineering, University of Toronto, Toronto, Canada; ^cDepartment of Management, University of Northern Iowa, Iowa, USA

ABSTRACT

Although many manual operations have been replaced by automation in the manufacturing domain in various industries, skilled operators still carry out critical manual tasks such as final assembly. The business case for automation in these areas is difficult to justify due to increased complexity and costs arising out of process variabilities associated with those tasks. The lack of understanding of process variability in automation design means that industrial automation often does not realize the full benefits at the first attempt, resulting in the need to spend additional resource and time, to fully realize the potential. This article describes a taxonomy of variability when considering the automation of manufacturing processes. Three industrial case studies were analyzed to develop the proposed taxonomy. The results obtained from the taxonomy are discussed with a further case study to demonstrate its value in supporting automation decision-making.

ARTICLE HISTORY

Received 3 September 2018
Accepted 22 June 2019

KEYWORDS

Variability; automation; taxonomy; manufacturing process; decision support



1. Introduction

Recent trends in production planning paradigms like mass customization to satisfy personalization of products and services for customers, while simultaneously decreasing the time-to-delivery, as well as a reduction of costs via process-/product-life-cycle considerations from cradle-to-grave are pushing for rapid technological developments (Foresight 2013). The technological developments manifest themselves in the production systems from planning and design to implementation of advanced control mechanisms. The latest example is the transition to Industry 4.0 by tracking, tracing and communicating via the 'internet of things' to address life-cycle considerations (Zeller and Achtenhagen 2010), as well as developments in Robotics and Autonomous Systems (RAS) with new control mechanisms to address variation and variability in areas, where human labour has been predominantly used. The reduction of manual labour and skill shortages in developed countries further drive the need towards the automation of more complex processes in modern production systems.

In many industrial sectors, automation has replaced manual operations that are dangerous, mundane, arduous and routine, for example in the transportation of heavy parts, stamping of large parts, repetitive welding and fastening. However, skilled operators still carry out critical manual processes in various industries such as aerospace, automotive

and heavy machinery. Related processes, such as component assemblies and finishing processes are difficult and costly to automate due to the variability present in the current processes (Thornton, Donnelly, and Ertan 2000). Typically, the operators must use both knowledge and skills to adapt and accommodate for variability in achieving the desired outcome (Sandom and Harvey 2004). Much research has been carried out in human factors, such as task complexity and ergonomics, and yet the influence of variability on the automatability and complexity of a process is still poorly understood.

Manufacturing variability has become a subject of extensive research but mainly for process and quality control. Manufacturing variability is defined as any inherent or unavoidable deviation from the nominal occurring in a manufacturing process (Apley and Shi 2001; Mantripragada and Whitney 1999; Zheng et al. 2008). A principal cause of variability suggested is the lack of robustness in production processes (Glodek et al. 2006). This variability may originate from different sources such as unplanned and undesired disparities, anomalies, inconsistencies or irregularities in the materials, equipment, operators, processes or environment that are not contemplated in the specifications. The National Institute of Standards and Technology (NIST) classified the types of variability into two categories: *controlled variability* and *uncontrolled variability*. Controlled variability is defined by a stable and consistent pattern of variation over time.

CONTACT Yee Mey Goh  Y.Goh@lboro.ac.uk  Wolfson School of Mechanical, Electrical and Manufacturing Engineering, Loughborough University, Loughborough, United Kingdom

© 2019 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.

This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Uncontrolled variability is distinguished by a pattern of variation that changes over time, and therefore, might be unpredictable [National Institute of Standards and Technology 2016].

As automation technology advances and becomes more flexible and intelligent (Bughin et al. 2017), for example, through the incorporation of advanced sensors, vision systems, machine learning algorithms and actuation strategies, the potential for automation of difficult and complex processes with greater variability increases. However, the decision to undertake automation is a complex one, involving the consideration of many factors such as return on investment (Chan et al. 2001), health and safety (Piggin 2005), life cycle impact including reliability, availability and maintainability (Birkhofer et al. 2010), competitive advantage (Lohse et al. 2005) as well as resources and technology availability (Rawat et al. 2014). Anecdotal evidence suggests that automation solutions have often overlooked variability in the process (because operators are much more adaptable than automation systems) leading to automation failure (right first time), lack of trust and added costs.

Therefore, an understanding of the variability sources during the execution of manufacturing processes is crucial in designing automated solutions (Antony et al. 2000). *The research hypothesis is that a systematic study of process variability, prior to a decision on whether to automate or not, identifies crucial requirements for the automation solution.* This article reviews the literature in task complexity and automation to identify key parameters/sources related to variability and then presents a taxonomy to categorize variability in manufacturing processes based on three case studies. A taxonomy, in general, is concerned with classification and schematization of a topic or area and aims to arrange related terms and concepts around it (Venter and Eloff 2003). This taxonomy is intended as a first step to support automation decision making by using variability information to later determine the complexity and cost of an automation solution. The usefulness of the taxonomy was demonstrated and evaluated with a case study of a free-form fastener automation application.

2. Literature review

The intricacy of manufacturing systems increases due to current trends in customized products and rises in product complexity (Satchell 1998). Thus, human skill is an important asset in manufacturing processes, and as such skilled operators and automated systems are essential for achieving flexible and productive manufacturing environments. Variability in manual manufacturing processes has been reported in the literature under various topics, depending on the purpose of these studies. Due to the cross-disciplinary nature of the research, this section first reviews the literature in the areas of manufacturing automation and task complexity (human factors) to study the impact of variability in manufacturing processes. Then research into automation design is covered to establish if these parameters have been considered in

research, particularly how the variability might influence the levels of automation.

2.1. Manufacturing flexibility and adaptability

Variability is considered an important factor in the manufacturing automation domain. Evidence can be found in different approaches of the industry to cope with variability in manufacturing processes. Traditionally, various methodologies have been used to control manufacturing variability relying on condition monitoring and process redesign. Examples can be found in methodologies such as Statistical Process Control (Apley and Shi 2001; Loose, Zhou, and Ceglarek 2019), Total Quality Management (Montgomery) or Six-Sigma (Dai and Yang 2011). Typical approaches involved eliminating variability by very tight tolerances for standard automation to be possible but at the expense of quality control costs and reduced flexibility.

From a hardware perspective, different solutions are used in the manufacturing industry to counter the variability such as industrial robots and other automatic systems. Two issues are repeatedly reported for robotics and automation systems. Poor positioning accuracy is one of the current problems to overcome variability in the automation process (Jamshidi et al. 2009). A second problem is related to the technology capabilities in terms of accuracy, tolerance, physical limitations (loads, momentum, forces, temperature), as well as product/process complexity (Kihlman 2005).

The robustness of the automated solution can be increased by corrective actions and error compensation algorithms (Jamshidi et al. 2009), which could be effective if the source of variability is known coupled with live metrology. Hardware limitations can be overcome by introducing systems that are flexible and adaptive to the environment by 'learning' from previous experiences. Artificial intelligence can be applied to 'imitate' human-like capabilities to analyze, learn, and react to novel situations and to deal with complex engineering problems such as dealing with variability (Dixit and Dixit 2008). Artificial Intelligence (AI) includes methods like neural networks, fuzzy logic, particle swarm optimization, genetic algorithms and ant colony optimization, which are commonly used in the RAS research domain.

Adaptive Automation, as an example, is based on the allocation of tasks between the operators and automation that is dynamically adjusted according to task demand user capabilities, total system requirements, and optimal system performance. Conceptually, the principal advantage of adaptive automation is that operator workload and fatigue can be managed by shifting the level of automation (Byrne 1996). Sauer et al. (Sauer, Nickel, and Wastell 2013), for instance, found that adaptable automation provided advantages over low and intermediate static automation with operators preferring higher levels of automation under noise than under quiet conditions. On the other hand, some studies have found operators may have a preference for less automation and preservation of manual control due to their aspiration for decision-making authority (Chmiel, Fraccaroli, and Sverke 2017).

A different automation approach focuses on ‘symbiotic technologies’ by supporting human physical and cognitive capabilities (Boff 2006). Proposed automation design should balance the strengths and weakness of humans and machines in a distributed system of information processing communication, decision and control. The researchers argue in favour of symbiotic approaches rather than automating all that can be automated and leaving the rest to workers or automating all that is found difficult by operators. Therefore, an upgrade of operators’ physical and cognitive capabilities is suggested via machine assisted aid. According to the authors, it is evident in a modern manufacturing process that a more efficient balance between human capabilities and machines is needed (Boff 2006). This article identifies variability in the processes, which could lead to further exploration to understand the right balance of automation from human performance perspectives. Madsen and Mikkelsen (Madsen and Mikkelsen 2018) argue in favour of training and learning programs to decrease severe productivity decreases when introducing more automation and high technology into activities that have been predominantly executed by humans.

A different perspective was taken by Burger et al. (Burger et al. 2017), who have developed a framework to identify specific flexibility types in manufacturing systems to enable matching with implicated challenges, like variability. Further, Demartini et al. (Demartini et al. 2017) identified and defined possibilities of improving Manufacturing Execution Systems by incorporating digitalized support to achieve the required flexibility. Despite digitalization being used as a response to flexibility issues, some experts have raised concerns about the introduction of digitalization technologies, including organisational requirements to establish an analytics unit, the identification and rapid deployment of analytics technologies (sometimes without due diligence), implementation

cost reviews, and cybersecurity (Fatorachian and Kazemi 2018). A study of the impact of flexible systems in the U.S. has demonstrated that specific flexibility dimensions, such as routing flexibility, material handling flexibility, and automation flexibility enable significant improvements in specific operational performance metrics (El-Khalil and Darwish 2019).

However, to further improve flexibility through automation, the understanding of process variability should be extended to facilitate decision making on an appropriate level of automation for manufacturing issues. Inadequate research has been carried out to investigate the impact of variabilities on the levels of automation undertaken with an organization.

2.2. Task complexity

In human factors research, task description and definition have received much attention due to direct influences on human performance. When considering automation, the complexity of tasks is one of the key factors to reflect upon (Bailey and Scerbo 2007; Wang, Sowden, and Mileham 2013). Based on the literature, the parameters used to describe variability and those which have been identified to influence the task complexity have been categorized and shown in Table 1.

Although it has been shown that humans might introduce variability in a manufacturing process (Sandom and Harvey 2004; Digiesi et al. 2009), the human’s capability of managing various sources of variability is also well documented. The capability is afforded from our ability to adapt to external conditions, as well as making decisions accordingly and consequently, to accomplish tasks that otherwise would be impossible to be completed within the established time and

Table 1. Parameters to describe variability from literature, adapted from (Ham, Park, Jung 2011; Liu and Li 2012).

Variability parameters important in task complexity	Papers
Number of elements	(Baccarini 1996; Rouse and Rouse 1979; Williams and Li 1999)
Number of information cues, information load	(Campbell 1988; Ho and Weigelt 1996; Harvey and Koubek 2000; Wood 1986)
Number of products/outcomes	(Ham, Park, and Jung 2011; Gardner 1990)
Variety/diversity of elements	(Marshall and Byrd 1998; Bonner 1994)
Presentation heterogeneity	(Campbell 1988; Wood 1986; Xiao et al. 1996; Williams 1999; Bell and Ruthven 2004; Carey and Kacmar 1997)
Uncertainty	(Baccarini 1996; Rouse and Rouse 1979; Campbell 1988; Wood 1986; Bonner 1994; Williams 1999; Boag et al. 2006)
Connectivity/relationship	(Campbell 1988; Harvey and Koubek 2000; Bonner 1994)
Number of paths/solutions	(Payne 1976; Kim and Khoury 1987; Payne, Bettman, and Johnson 1992)
Number of alternatives	(Wood 1986; Speier 2006; Xu et al. 2009; Zhang et al. 2009)
Number of operations/sub-tasks/acts	(Harvey and Koubek 2000; Bonner 1994; Byström and Järvelin 1995; Nadkarni and Gupta 2007; Mascha and Miller 2010; Skjerve and Bye 2011; Liu and Li 2012)
Structure/specification/clarity	(Harvey and Koubek 2000; Schwarzwald, Koslowsky, and Ochana-Levin 2003)
Repetitiveness/non-routinely	(Xiao et al. 1996; Skjerve and Bye 2011; Liu and Li 2012; Molloy and Parasuraman 1996; Hendy, Liao, and Milgram 1997)
Concurrency	(Payne, Bettman, and Johnson 1992; Skjerve and Bye 2011; Liu and Li 2012; Greitzer 2005; Svenson and Edland 1987; Klein 1993; Hendy, Liao, and Milgram 1997)
Time pressure	(Liu and Li 2012; Greitzer 2005; O'Donnell and Johnson 2001; Steinmann 1976)
Format/mismatch/inconsistency/compatibility	(Liu and Li 2012; Greitzer 2005; Hendy, Liao, and Milgram 1997)
Difficulty	(Bailey and Scerbo 2007; Campbell 1988; Liu and Li 2012; Campbell and Gingrich 1986; Sintchenko and Coiera 2003)
Cognitive demand	(Bailey and Scerbo 2007; Campbell 1988; Liu and Li 2012; Campbell and Gingrich 1986; Sintchenko and Coiera 2003)
Physical demand	(Ham, Park, and Jung 2011; Gardner 1990)

quality standards (Sandom and Harvey 2004). Automation systems lack this unique attribute at a reasonable cost and speed, even with the latest sensors and machine learning technologies (Zeller and Achtenhagen 2010; Venter and Eloff 2003).

Where a human-machine system is to be implemented, it might be beneficial to investigate the reliability of the automation aid as well as the performance of subjects with different levels of reliability of the automation aid. Reliability and accuracy of automated support have a significant effect on performance, false alarms decrease performance more than true misses (Levinthal and Wickens 2006). However, subjects do not always rely on the recommendations of the automated solution, frequently ignoring raw data (Dixon and Wickens 2006) and consequently, unreliable automation solutions were found to reduce performance (Rovira, McGarry, and Parasuraman 2007). The findings suggest giving operators greater access to data and to inform operators about the reliability of the system so as to improve the outcome (Wang, Jamieson, and Hollands 2009; Satchell 1998).

The investigation of complexity driven parameters has led to the understanding that quantification of variability in a process has not yet been fully understood and some of these parameters may be interdependent. Also, some of the research motivation was in improving human performance and not undertaken with a view of automating the process. While not all aspects of task complexity are relevant to automation, certain aspects directly influence the sophistication of automation technology, for example, advanced sensing and artificial intelligence. Studies established different parameters to characterize complexity during the execution of tasks (Glodek et al. 2006; Wang, Sowden, and Mileham 2013; Thornton 1999; Doerr and Arreola-Risa 2000; Antony, Hughes, and Kaye 1999), and (Wood 1986; Liu and Li 2012; Schwab and Cummings 1976; Gutenberg et al. 1983; Lohse 1997).

2.3 Levels of automation

In relation to variability, the authors investigated studies measuring human performance for tasks assisted by some form of automation. For some manufacturing processes, forms of physical/mental support appear to be plausible solutions (human-machine system). A high variety of automation aided solutions exists ranging from a robotic arm interface (Park and Woldstad 2000), a flight simulator (Mosier et al. 2007), search and rescue tasks (Wang, Lewis, et al.

2009) to victims location and team collaboration (Wang, Chien et al. 2009). These studies document highly demanding tasks, requiring additional subject responses, to have a negative impact on performance. Some studies also indicated the relationships between performance and workload. For example, less time to perform a task increased performance, but it also augmented the workload and error rate (Mosier et al. 2007).

Fitts was the first to consider the incorporation of machines in manufacturing and how human-machine tasks occurred in manufacturing environments (Fitts 1951). He categorized tasks according to a relative performance by humans and machines to allocate functions to machines or humans. The approach is commonly known as a Fitts' list approach and contains concepts still valid today (de Winter and Dodou 2014), although more recent approaches seek a collaborative function allocation between humans and machines rather than separation (Feigh, Dorneich, and Hayes 2012).

When the complexity of tasks increases, it is necessary to dynamically manage the workload of operators to preserve a performance optimum. Therefore, it is critical to choose the appropriate level of automation, depending on the nature of the tasks and the reliability of the automated solution. Automation design decisions are extremely important as disproportionate levels of automation may be detrimental to operator performance (Parasuraman, Sheridan, and Wickens 2000; Chmiel 2008). Consequently, finding the right Level of Automation (LoA) to apply is critical. Table 2 shows a selection of definitions for LoA.

According to Williams and Li (Rouse and Rouse 1979), automation can be divided into mechanization and computerization. Most tasks within manufacturing processes present a mix of both mechanization and computerization. Taking into consideration these two aspects, automation in manufacturing should be considered as an interaction between physical tasks and cognitive tasks. Frohm et al. (Frohm et al. 2008) proposed a classification composed of seven different levels, considering two separate scales associated with the two types of level of automation, physical and cognitive as seen in Table 3.

This classification takes into consideration both physical and cognitive actions separately. In contrast to other models, it organizes actions into two types: mechanization (physical) as well as information and control (cognitive) allowing the assessment of an independent LoA for both types of actions. If the lowest level of automation is completely manual and

Table 2. Different level of automation definitions.

Level of automation definition	Reference
The level of automation ranges from direct manual control to autonomous operation where the human intervention is minimal.	(Billings 1997)
The level of automation is defined as the division between the human and machines with different grades of human implication.	(Satchell 1998)
Level of automation is a progression from manual to fully automatic operations.	(Parasuraman, Sheridan, and Wickens 2000)
The level of automation is an amount of the human level of implication around the machines, which can be either manually operated, semi-automated, or fully automated.	(Groover 2007)
The distribution of physical and cognitive tasks between humans and technology, varying from totally manual to totally automatic	(Frohm et al. 2008)

Table 3. Classification of the level of automation according to Frohm et al.

LoA	Mechanisation	Information and control
1.	Totally manual. No tools are used, only the users own muscle power, e.g. the users own muscle power	Totally manual. The user creates his/her own understanding of the situation and develops his/her course of action based on his/her earlier experience and knowledge, e.g. the users earlier experience and knowledge
2	Static hand tool. Manual work with the support of a static tool, e.g. screwdriver	Decision giving. The user gets information on what to do or proposal on how the task can be achieved, e.g. work order
3	Flexible hand tool. Manual work with the support of a flexible tool, e.g. adjustable spanner	Teaching. The user gets instruction on how the task can be achieved, e.g. checklists, manuals
4	Automated hand tool. Manual work with the support of an automated tool, e.g. hydraulic screwdriver	Questioning. The technology questions the execution if the execution deviates from what the technology considers being suitable, e.g. verification before action
5	Static machine/workstation. Automatic work by a machine that is designed for a specific task, e.g. lathe	Supervision. The technology calls for the users' attention, and direct it to the present task., e.g. alarms
6	Flexible machine/workstation. Automatic work by a machine that can be reconfigured for different tasks, e.g. CNC-machine	Intervene. The technology takes over and corrects the action if the executions deviate from what the technology consider being suitable, e.g. thermostat
7	Totally automatic. Totally automatic work, the machine solves all deviations or problems by itself, e.g. autonomous systems	Totally automatic. All information and control are handled by the technology. The user is never involved, e.g. autonomous systems

the highest level of automation is fully automated, studies have demonstrated intermediate LoA to entail a superior performance (Manzey, Reichenbach, and Onnasch 2008; Lorenz et al. 2002) and decrease the operators' workload (Röttger, Bali, and Manzey 2009). Being dependent on automation makes operators highly vulnerable to situations of system crashes and the degree of their reliance will increase the magnitude of the impact proportionally (Reichenbach, Onnasch, and Manzey 2011).

Resulting from the previous discussion, a distinct determination of complex tasks for operators is important before deciding what to automate. In making such a decision, it is key to have an understanding of what makes a task complex and what parameters have been defined by researchers to characterize task complexity. A lack of connection between research in task complexity and human factors regarding variability in research conducted in automation was observed. There is an increasing concern within the literature that some automation projects are being disadvantaged by a lack of understanding of the remaining variabilities driven by current manual processes (Goodrich and Boer 2003).

However, the authors are not aware of any systematic consideration of variability as identified in task complexity in the automation literature. This article attempts to link these fields by bringing the study of variability into automation of processes as an additional variable to be taken into consideration for a process being considered for automation.

3. Research methodology

In order to categorize variability, task complexity models have been used as a starting point to investigate the key parameters. Variability has been identified as one of the root causes contributing to task complexity, and in the literature is labelled as either uncertainty (Campbell 1988; Wood 1986; Xiao et al. 1996; Williams 1999; Bell and Ruthven 2004; Carey and Kacmar 1997) or variability (Liu and Li 2012; Greitzer 2005; O'Donnell and Johnson 2001; Steinmann 1976). The taxonomy was developed based on

the parameters found in the literature on task complexity and the parameters relating to variability are then categorized into five key attributes based on three industrial processes studied. This step was necessary due to missing parameters categorizing variability in the literature, and to translate the terminologies used in task complexity into the manufacturing automation domain.

Although the operators would introduce variability in manufacturing processes by the mere fact of being humans (Sandom and Harvey 2004), this paper does not focus on an in-depth investigation of variability found between individuals due to a range of internal and external human factors.

Internal factors are, among others, age, gender, race, culture, education, physical condition, cognition, tiredness, motivation, social factors and human relationships inside/outside the workplace. External factors are outside scope of this paper and include environmental conditions (light, cold, noise) or constraints, such as time, space, as well as social factors and organizational factors (Digiesi et al. 2009). It is assumed that human variability will be observed as an intrinsic part of the manual process.

On completion of the taxonomy development, a fourth case study was used to apply the created taxonomy to a real-case scenario to demonstrate the purpose and value of the taxonomy in automation decision making.

3.1. Identification of variability parameters

A literature review revealed a set of parameters identified from task complexity that might be used to describe variability (shown in Table 1). With the objective of extracting parameters suitable to describe variability, the parameters were applied to study variabilities introduced by three industrial processes. The three selected processes are heavily influenced by process variabilities and, therefore, contribute to the investigation. The processes investigated were grinding, de-burring and welding of high-value metallic components

(more information can be found in (Manorathna et al. 2017; Sanchez-Salas 2016)):

1. The first case study is related to a grinding process for aerospace components. The specific components of the grinding process are safety critical parts and have tight requirements in finishing quality and surface tolerances. The purpose of grinding is to achieve a smooth transition or flow of the surfaces on each component. The material removed in grinding processes must be kept to a minimum and the components' form should not be modified
2. From its original geometry as the flow among surfaces is critical to the functionality of the components. The component ground has multiple features and surfaces, including a slope, a joint and radii between surfaces. Multiple polishing wheels were made and changed according to the features ground, and they were also reconditioned by the operators during the process. Naturally, a grinding process is highly influenced by previous tasks and faces a high degree of in-process variability.
3. The principle of de-burring is to remove any sharp edges from the components, applying light pressure to generate smooth transitions between surfaces on the component without modifying the component's features at all. In this case study, the component is CNC machined from a raw material block to create specific design features, including holes, cavities, threads and surfaces with different inclinations and intersections. These features vary in terms of size, ranging from millimetres to a few centimetres. A single experienced worker would spend four to six hours per component. The work-cell contains a set of tools: two air compressed tools (one rotational and one blower), a tiny torch with light intensity regulator, a magnifying glass and different types of emery cloth, coarse files, needle files and fettling tools. In addition to this, two tubular lights are employed to provide extra illumination to the cell work while the operator works sitting facing the station. The deburring process is a reaction provoked by previous machining variabilities. In contrast to the grinding process, the defects are increasingly found on the features mentioned. However, an automation process must deal with the inflicted process variabilities of previous production processes at different part locations.
4. Gas Tungsten Arc Welding (GTAW) is a joining process, usually manually applied in aerospace applications, fusing two parts along with specific connection points or lines. Reasons for not automating the processes are mostly related to a lack of information about the process with high dimensions of complexity and its critical response to process variabilities (Park and Woldstad 2000). Commonly known, GTAW is mostly used for different alloys in aerospace applications as it provides superior welding joints compared to other welding connections. The gas shields joints against reactive environmental gases (like oxygen) and prevents undesirable

changes of material properties during the welding process. The need to automate these processes is driven by health and safety concerns related to the gas, heat and ergonomic concerns. A connection of the parts in this process is, hereby, fully established after cooling down the metal beyond the fusion temperature of the different material combinations.

In each of the manufacturing processes, the following methods were used to identify potential parameters that are important for consideration in the variability taxonomy:

- First, the main sources of variability in machines, materials, procedures and measurements are identified. The information was gathered from company documentation of product requirement, equipment, Standard Operating Procedures (SOP), supplier, quality and maintenance reports, customers' reports and warranty data.
- Next, observations were made, whilst the operators performed their tasks. Observation has been shown to be a powerful tool for studying manufacturing environments and its variations, related to processes or workers. In this research, a non-participant (the observer stands at a distance from the process being observed), direct (the researcher observes and takes notes in the facilities), overt (the observer knows that the researcher is watching) and structured observation (structured observation requires some previous research from the observer in order to delimit what is important to observe) was adopted. Structured observation was chosen as it the most suitable for the environment and the nature of the tasks observed.
- The processes were video recorded for further analysis and additional notes were made during the observation.
- After the observation of the expert operators performing the tasks, they were interviewed. In this study the interviews were semi-structured, using a mix of closed and open-ended questions. The interview process allowed the researcher to confirm quantifiable data (i.e. years of experience, tools used, number of pieces per batch) and to clarify some findings from the observations. The questions were subdivided into three categories: work experience, procedure and tools. Open-ended questions were used to explore qualitative information related to the operators' ideas and experiences in dealing with variability and potential automation solutions.

Table 4 summarises the variability parameters observed from the manual processes in the three industrial case studies.

Based on the findings from the three case studies, a new taxonomy was developed and is discussed in Section 3.2.

3.2. Proposed variability taxonomy: attributes and parameters

From the data collected and observations, the process was decomposed into key tasks and subtasks. By decomposing

Table 4. Variability parameters identified in grinding, de-burring and welding processes.

Parameter	Observed within the grinding process	Observed within the de-burring process	Observed within the welding process
Number of elements and number of information cues, information load	YES – grinding requires constant feedback from the process about part parameters to achieve an optimal surface quality.	YES – de-burring requires the identification of specific surface patterns, which need deburring. The number and types of features requiring deburring introduces variability.	YES – welding is influenced by many factors (current, potential, distance tip to parts, part temperature, material homogeneity/heterogeneity, etc.) which must be constantly monitored and fed back to the process control.
Number of products/ outcomes and Variety/diversity of elements	YES – for the investigated grinding process, various parts were ground requiring specific surfaces. A change of parts introduces variability based on actions that do not fully apply to other parts (compromising solutions).	YES – workers must identify faulty surfaces. If the variety of the parts is increased, the workers learning the process for a specific part with regards to more often occurring errors is delayed/does not take place and increases variability.	YES – as one of the most complex processes, the variability of the welding process is characterized by high variety and diversity of elements. Different forms and shapes require different approaches during the welding process (for example welding a straight line vs. welding a curve)
Presentation heterogeneity	YES – every part has specific surfaces that need to be ground to a specific surface quality. The part is constantly turned by the operator to work on 3D surfaces. The positioning accuracy of the part has significant influence on the variability for automating.	YES – the workers must re-orientate the parts during the process to check specific edges. A specific position is, therefore, necessarily required and is found to impact on the variability of the results.	NO – challenging manual welding processes require the operator to weld from different angles and orientations around the part. No evidence was found for the orientation of parts to impact on the variability.
Uncertainty	YES – the previous manufacturing processes may produce varying surface finish for every part and introduce uncertainty to the grinding process to achieve the required surface quality.	YES – the burrs created from the previous machining processes may be uncertain in shape, location and size.	YES – the uncertainty in those factors affecting the welding process has to be managed to reduce the variability of the process outcome.
Connectivity/relationship	YES – the roughness and shape of the abrasive grinding wheel changes due to the grinding process, which affects the pressure applied. This dependency will introduce variability in the production process if not monitored.	YES – similar to grinding, the tool properties change, and multiple tools required will affect how the process is performed.	YES – welding introduces high temperatures in the related part. Welding a curve, for example, introduces additional heat into neighbouring welding zones. The adaption of current, potential and distance to the parts with respect to the form of the weld and the neighbour zones affects variability.
Number of paths/ solutions and number of alternatives	YES – the production process can be performed starting with different surfaces of the part first. Especially at the transition edges and points of the part surfaces, this might lead to variabilities of the processed part.	NO – there is a strong relationship between the process and the burrs identified. An identification of a specific burr drives a specific solution and, consequently, does not introduce variability.	NO – It is important for the welding process from which point the weld starts in terms of the weld quality. The starting point, therefore, has an impact on the variability of the weld but is usually consistently applied.
Number of operations/ sub-tasks/acts	YES – the higher the number of sub-operations, the more likely it is to compromise the results of the production process due to process/ human errors.	YES – the higher the number of operations due to surface defects or transitions, the longer the process time and increased likelihood of human and/or process errors.	YES – the higher the number of operations due to the specific shape of the welding area, the longer the specific process time and the likelihood of human errors/and process errors.
Structure/ specification/clarity	NO – grinding is guided by the goal for achieving smooth surface finish and transition. Structuring the process in specific ways or increasing/decreasing clarity of the process was not found to impact the results.	NO – different structures and clarifications of the process and related defects of the surfaces did not affect the outcome of the variability.	NO – for the manual process, the welders use their experience to achieve their best welds. The welding process does not require additional measures of structure or clarity to produce desired results.
Repetitiveness/ non-routine	YES – the repetitiveness and routines used lead to a reduction of process variability as workers learn from their experiences and the given feedback on the quality control.	YES – When more routine was added to the de-burring process, learning effects seemed to reduce the introduced variability.	YES – when more routine was added to the welding process, learning effects of seasoned operators seemed to reduce the introduced variability to a certain extent.
Concurrency	YES – multi-tasking is found to lead to a lack of focus for a specific action resulting in an increased variability in the production processes.	YES – a more reasonable strategy is to focus on one surface defect after another to reduce the cognitive strain on the operator and reduce the variability.	YES – the control of the complex welding problem leads to variability within the welding of the parts. This is due to the number of parameters that must be managed simultaneously.
Time pressure	YES – time pressure increases mental and cognitive strain on workers. The workers have less time to investigate surface quality during the process. An increase of time pressure was reported to have a substantial impact on the variability in quality of the grinding surfaces.	YES – time pressure increases mental and cognitive strain on workers. It also affects tool degradation and in process inspection.	YES – having to weld faster will lead to an increase in potential and current used with all the implications for the welding zone. Time pressure is found to increase the variability of the weld.
Format/mismatch/ inconsistency/ compatibility	NO – inconsistencies and mismatches mainly appear within processes requiring different technologies or procedures. Grinding process is	NO – the deburring process is not an application of different interacting technologies and, therefore, does not	NO – inconsistencies and mismatches mainly appear within processes requiring different technologies or procedures to interact with each other.

(continued)

Table 4. Continued.

Parameter	Observed within the grinding process	Observed within the de-burring process	Observed within the welding process
	affected by a change of abrasive surfaces that are custom made by the operators. The change of abrasive materials was not found to introduce inconsistency/compatibility driven variabilities.	drive variability issues for the product from a manual perspective.	This does not apply to the welding process.
Difficulty	YES – complex parts, for example, small turbine plates with several critical surfaces have an impact on the introduced variability. The more complex the part was, the larger the reported variability if no countermeasures were introduced (for example additional process time).	YES – the location, size of the burrs and surface defects influence the difficulty of the manual de-burring process. The quality of the product improves if the burrs and defects are accessible by the operator and tool.	YES – the location of the welding spots influences the difficulty of the process. The quality of the product improves if the weld is easily accessible by the operator and tool. It reflects on the variability of produced quality.
Cognitive demand/difficulty	YES – an increase in cognitive demand intensifies the mental strain on the worker and the processing effort/time. Grinding requires the full attention of a worker and can lead to scrap if part tolerances are exceeded.	YES – high cognitive demand, especially for inspecting burrs, has been reported for deburring. The high value component also requires careful treatment and handling of the parts.	YES – high cognitive demand was found for welding due to managing many factors dynamically.
Physical demand	YES – an increase in physical demand shortens the time until the workers feel tired or exhausted, which leads to a lack of focus and increase the introduced variability. Vibration is key concern.	YES – the complex part requiring intricate manipulation and inspection.	YES – welding was found to be physically demanding due to accurate motor controls.

the process, it is possible to determine in which specific task the variability is introduced into the process and how the operator accommodates this variability. The process is represented using an IDEF0 diagram. The IDEF family models represent different views of a system. IDEF0 produces a structured functional model to gain understanding, support analysis, provide logic for potential changes, specify requirements, or support systems-level design and integration activities (U.S. Department of Commerce 1993).

An IDEF0 diagram describes what a system does, what controls it, what things it works on, which means it utilizes to execute its functions, and what it delivers. The components in the IDEF0 are: inputs (I), controls (C), outputs (O) and mechanisms (M). Input data or objects are transformed by the function to produce the output. A control is utilised to address the work in the process. Plans, standards and checklists are all forms of control. Mechanisms can be staff, tools or equipment employed to carry out a task. The variability parameters identified from Section 3.1 contributing to variability in manufacturing processes are associated with five key attributes of the task: *inputs, outputs, strategy, time* and *requirements*. *Strategy* and *Time* are defined as forms of control that determine the way the tasks were executed, and *Requirements* refer to the mechanisms that enable the task to be performed.

Table 5 shows interlinks between the related terms to determine and classify a taxonomy via attributes as well as related variability parameters and maps them against equivalent terms used in the literature. Similar concepts have been grouped and common definitions are used, which are consistent with the manufacturing domain. For example, in the literature different models describe ‘uncertainty’ or ‘presentation heterogeneity’ as parameters for complexity. These have been assigned to ‘range or interval’ in the taxonomy.

Based on the three industrial case studies, a taxonomy for manufacturing automation variability has been developed, with the aim of supporting automation decision-making, and this has been summarised in Figure 1. As the figure suggests, the five important attributes can be further decomposed into a number of variability parameters, and the levels of variability related to each of these parameters will need to be considered for deciding the right level of automation for the task.

The proposed taxonomy is applied and evaluated using an automation case study where the solution has been designed independently. Decision support for automation capability of the proposed variability taxonomy is demonstrated using the Analytic Hierarchical Process (AHP) to suggest suitable levels of automation for the tasks based on variability information.

4. Evaluation of proposed taxonomy

A case study of automated fasteners assembly in a non-structured environment is used to illustrate the application of the proposed taxonomy. Fastening is a relatively simple assembly process for a human operator to perform, but it is a very complex process to automate (Dharmara et al. 2018). Additionally, the selected process shows no similarities to the case studies selected for the development of the taxonomy. Currently, most fastener assemblies are carried out either by human operators with tightening tools or by repetitive automation with complicated fixtures. Some of the identified variabilities in this process include the different size of bolts, the location and angular position of the mating threaded holes, the torque required for the bolts, and the way the fasteners are presented to the system (separated or clustered in a bin). These variabilities present significant challenges on the identification, localization and grasping of

Table 5. Attributes and parameters used in the taxonomy.

Attribute	Parameter	Definitions	Equivalent in literature
Inputs/Outputs	Quantity	Identifying the number of variability sources that will affect the related inputs/outputs	Number of elements (Baccarini 1996; Rouse and Rouse 1979; Williams and Li 1999) Number of information cues, information load (Wood 1986; Bonner 1994; Carey and Kacmar 1997; Zhang et al. 2009; Steinmann 1976; Simnett 1996; Hartley and Anderson 1983; Asare and McDaniel 1996)
	Diversification	The number of different types of outputs/inputs affected by variability. One source of variability could affect different outputs/inputs.	Number of products/outcomes (Campbell 1988; Ho and Weigelt 1996; Harvey and Koubek 2000; Wood 1986) Variety/diversity of elements (Ham, Park, and Jung 2011; Gardner 1990)
	Interval or range	Delimiting sources of variability to the range of the unwanted deviation.	Presentation heterogeneity (Marshall and Byrd 1998; Bonner, 1994) Uncertainty (Campbell 1988; Wood 1986; Xiao et al. 1996; Williams 1999; Bell and Ruthven 2004; Carey and Kacmar 1997)
	Interdependency	Evaluation of the dependency of two or more sources of variability. Dependent: the effect could be either positive or negative: <ul style="list-style-type: none"> Positive (reducing or eliminating one source of variability will reduce or eliminate the other source of variability). Negative (reducing or eliminating one source of variability will increase the other source of variability). Independent: one source of variability will have no effect on other sources of variability.	Connectivity/relationship (Baccarini 1996; Rouse and Rouse 1979; Campbell 1988; Wood 1986; Bonner 1994; Williams 1999; Boag et al. 2006)
Strategy	Number of alternatives	The number of different paths/approaches followed to complete a task.	Number of paths/solutions (Campbell 1988; Harvey and Koubek 2000; Bonner 1994) Number of alternatives (Payne 1976; Kim and Khoury 1987; Payne, Bettman, and Johnson 1992)
	Number of actions	The actions executed to overcome variability in a task.	Number of operations/sub-tasks/acts (Wood 1986; Speier 2006; Xu et al. 2009; Zhang et al. 2009)
	Pattern	The repeated actions during the task could follow a pattern.	Structure/specification/clarity (Harvey and Koubek 2000; Bonner 1994; Byström and Järvelin 1995; Nadkarni and Gupta 2007; Mascha and Miller 2010; Skjerve and Bye 2011; Liu and Li 2012) Repetitiveness/non-routine (Harvey and Koubek 2000; Schwarzwald, Koslowsky, and Ochana-Levin 2003)
Time	Concurrency	Concurrency refers to how the sources of variability are introduced during the execution of the task with regards to 'time'. Sequential: if they are introduced in different actions. Concurrent: when they are introduced during the same action and managed simultaneously.	Concurrency (Xiao et al. 1996; Skjerve and Bye 2011; Liu and Li 2012; Molloy and Parasuraman 1996; Hendy, Liao, and Milgram 1997)
	Time availability	Time availability refers to the time allocated in the manual task to either eliminate variability or to reduce it to an admissible range.	Time pressure (Payne, Bettman, and Johnson 1992; Skjerve and Bye 2011; Liu and Li 2012; Greitzer 2005; Svenson and Edland 1987; Klein 1993; Hendy, Liao, and Milgram 1997)
Requirements	Sensorial	The domain of sensorial features required to detect variability, i.e. sight, hearing, taste, touch and smell.	Format/mismatch/inconsistency/Compatibility (Liu and Li 2012; Greitzer 2005; O'Donnell and Johnson 2001; Steinmann 1976)
	Cognitive requisite	Cognitive requisite attempts to highlight any mental process required to evaluate and react to variabilities, such as analysis, judgement, assessments and problem-solving skills.	Difficulty (Liu and Li 2012; Greitzer 2005) Cognitive demand (Bailey and Scerbo 2007; Campbell 1988; Liu and Li 2012; Campbell and Gingrich 1986; Sintchenko and Coiera 2003)
	Physical requisite	Any physical attribute to deal with variability, for instance: accessibility, tools, force, torque or, environmental conditions.	Physical demand (Bailey and Scerbo 2007; Campbell 1988; Liu and Li 2012; Campbell and Gingrich 1986; Sintchenko and Coiera 2003)

fasteners for the automation system. The human operator can adapt to these variabilities with their dexterity to handle the fasteners and match them to the correct holes (real-time decision making and process modifications).

The proposed variability taxonomy is applied to this case study and the results are compared to an independently

developed automation solution. Figure 2 shows the experimental setup of the case study from Dharmaraj (Dharmaraj 2015). The case study scenario proposed for freeform fastener assembly involving assembling different size bolts into their corresponding size threaded holes in a non-structured environment. To replicate a real case scenario in the

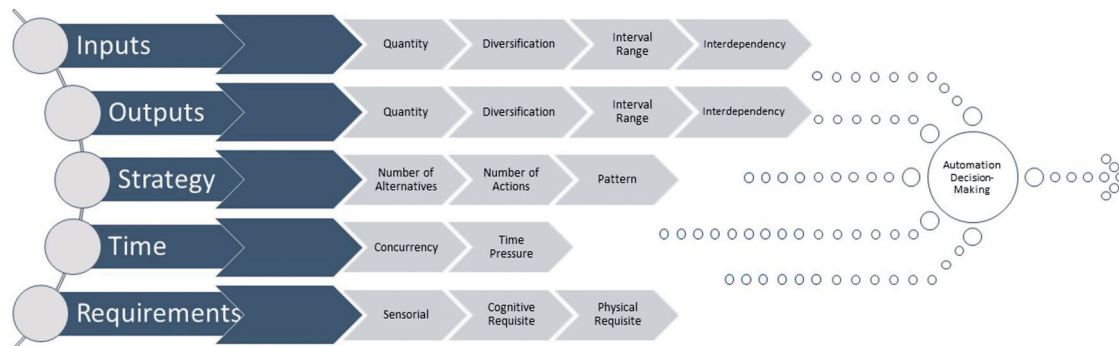


Figure 1. Variability taxonomy proposed.

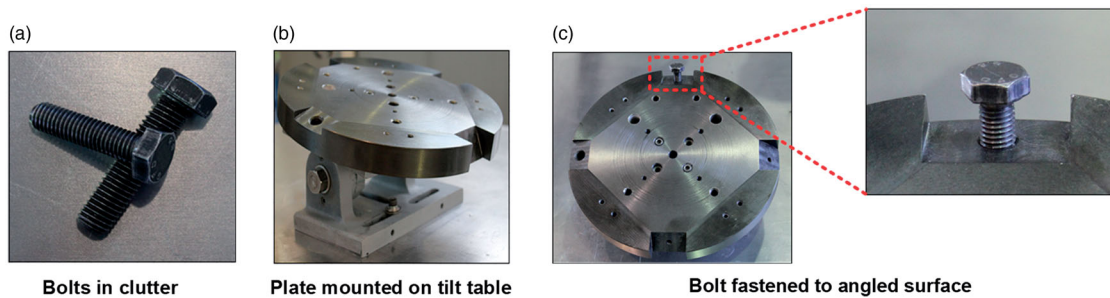


Figure 2. Non-structured threaded fastener assembly (Dharmara et al. 2018), licensed under <http://creativecommons.org/licenses/by/4.0/>.

laboratory, a disc with various sizes of threaded holes was mounted on a tilting table to illustrate a random position of the holes in 3D space. Various numbers of corresponding bolts were located in a bin, representing a non-structured environment. An automation system was developed to select and pick the correct bolt and fasten it to the correct threaded hole in an unknown position on the disc.

The investigation starts with analyzing the inputs and outputs of the fastening process. Based on the inputs and outputs, the strategic part can identify alternatives and actions to address the variabilities. A determination of time constraints allows a clearer picture of the later automation systems design and supports the conclusion towards physical and cognitive requirements for the fastener assembly process. The variability parameters are further explained in the following subsections.

4.1. Application of proposed taxonomy

The proposed taxonomy has been applied to the case study to identify key variabilities to be considered for automation. Figure 3 presents the overall IDEF0 representation for the case study to graphically illustrate the variability and parameters for the 5 main tasks, as described below.

4.1.1. Input and output

The 16 different input variabilities identified are related to the size of bolts and threaded holes, the initial positions of bolts and threaded holes as well as colours and materials. For the automation solution, these input variabilities for all the screw sizes (=144 input variabilities) must be addressed. All the included variabilities but the material and colour are multidimensional variabilities.

Before those variabilities are investigated, all combinations are considered possible. The next step is to numerically identify the range of the variabilities. If the variabilities do not exceed a critical value, the dimension of variability can be reduced. In this example, the screw sizes and threaded hole sizes are according to the related ISO standards. Therefore, the application challenge is reduced by the three screw head dimensions, body dimensions of both screw and threaded hole, as well as the pitch dimension of the screw and threaded hole. This leaves *four remaining dimensions as possible sources of variability*. The remaining dimensions are related to the location dimensions of both, the screw and the threaded hole.

4.1.2. Strategy

The initial step has determined the critical input and output variables based on an investigation of the quantitative number, the diversification, the interval range and, finally, the interdependency of the parameters. Based on this investigation, the authors extract knowledge about four critical variabilities in the process.

For the location of the feature and the object, as well as for the alignment of the task, a careful distinction must be made about the alternatives. For the manual process, the perception sense required can be identified as visual perception. However, from an automation systems perspective, two possible solutions are possible. Either a 2D and a 3D vision system application could be selected. Five overall tasks are identified as part of the manufacturing process. The identified tasks of the threaded fastener assembly are feature detection to find the hole, object identification to recognize the screw, pick and place to pick and align the screw with the threaded hole, object insertion and automated fastening.

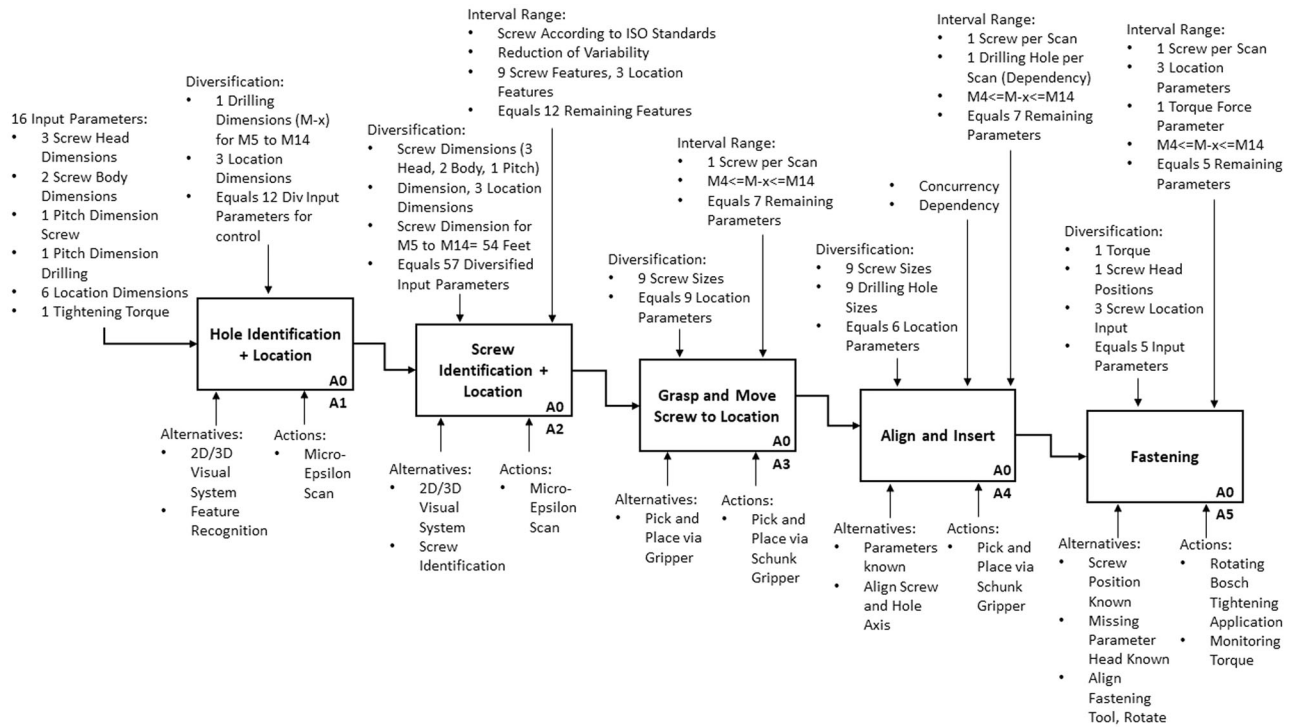


Figure 3. IDEF0 diagram for threaded fastener assembly.

Table 6. Final weight utilized in the decision support.

Attribute	Parameter	Weights			
		Expert 1(%)	Expert 2(%)	Expert 3(%)	Average(%)
Input/Output	Quantity	5.10	4.30	8.54	6.0
	Diversification	6.4	5.7	6.6	6.2
	Interval range	20.1	25.0	22.0	22.4
	Interdependency	2.1	4.7	4.1	3.6
Strategy	Number of alternatives	1.7	2.3	2.4	2.1
	Number of actions	1.7	1.4	1.3	1.5
	Pattern	1.7	2.0	2.4	2.0
Time	Concurrency	4.6	8.6	6.1	6.4
	Time availability	23.4	24.8	14.9	21.0
Requirements	Sensorial	5.8	2.4	5.8	4.7
	Cognitive prerequisite	13.7	11.3	17.0	14.0
	Physical prerequisite	13.7	7.6	9.0	10.1
	Total	100	100	100	100

Additionally, the automated assembly task has been identified as a task with a repetitive pattern. The identified movement is a helix-formed movement.

4.1.3. Time

The strategic step now has evaluated how to approach the remaining introduced variabilities. Two alternatives for the required perception, 2D and 3D visual feedback, have been identified to complete 5 key tasks. The 3D vision system will need to process more data and therefore will be slower. The following attribute of the taxonomy, therefore, investigates the time constraints.

Even though no time pressure was applied to the testing of this application within the project, there might be a time pressure in a real-life scenario. This time pressure might be driven by the applied tact time of the production process. However, as part of the application, alignment and the tightening process must be checked continuously. These time constraints

drive specific requirements for the control system of the process. The complexity of two simultaneously working systems, especially for the perception, might increase proportionally (Herrmann 2015). At a specific moment, multiple factors are introduced at the same time, the application engineer must decide which process control to use. Two different ways of automation were possible. A set of sensors could either constantly monitor the process or a single sensor only monitors a specific state of the process as an active sensor before a state transition allows the sensor to switch into a passive mode. Even though constant monitoring of all sensors might be easier to set up as no logic is required, such a solution creates issues with conflicting information and increases the power and data storage consumption/use.

4.1.4. Requirements

The information about the timing of actions can finally be used to inform the requirements of the application. Using the system

as a basis, the application engineer can design the overall action blocks and allocate physical resources to the specific process parts. The actions and alternatives informed requirements for the fastening application and determined the cognitive and physical requisites. Therefore, this step allows the determination of functional blocks and the design of components needed in terms of the sensorial requirements.

4.2. Automation decision support

In order to demonstrate the application of the proposed taxonomy, decision support based on the Analytic Hierarchy Process (AHP) process was used to determine a suitable level of automation for the fastener assembly automation. AHP is a well-established method to solve multi-criteria decision problems using a hierarchical structure of factors (Saaty 1990). In order to be able to compare variability and to provide a standardized value for the parameters described, a specific *weight* has been assigned to each parameter in the proposed taxonomy. The AHP transforms these one-to-one comparisons into a rank where these parameters are classified by weight (i.e. importance). The weights have been calculated from a survey completed by expert engineers working in the aerospace sector. The experts were asked to evaluate each parameter against the other through a parameter matrix. After obtaining the *weights* from the experts, the resulting weights were averaged. The weights for each parameter from the experts are shown in Table 6.

These weights are determined from the experience of the experts, so they are subjected to the user's perception. Their *weights* elicited in this article are limited to the targeted industry domain. Therefore, it is cautioned that readers should determine, or at least validate, the appropriate weights prior to the application of the decision support in different industries, using AHP or any other similar method. The variabilities, based on the application of proposed taxonomy in Table 5, are assigned a subjective score between 1 and 10 (1- low variability, 10-high variability) as shown in the results in Table 7. The weighted sum of the variabilities will be used to indicate a suitable level of automation.

The LoA scale proposed by Frohm et al. (Frohm et al. 2008) (as shown in Table 3), is used where Level 1 corresponds to a completely manual task and Level 7 concurs with full automation, where no human intervention or supervision is needed. In this article, the first two levels are discarded as they apply to rudimentary systems not found in the type of processes studied in this research and are therefore noted as "None" referring to the level of automation null or neglected. The remaining five levels have been grouped into four categories: *low* (levels 3 and 4), *moderate* (level 5), *considerable* (level 6) and *high* (level 7); the levels are defined in Table 3. A low score of variability indicates suitability for a *high level* of automation and a high score indicates a *low level* of automation. The variability scores are equally divided into 5 classes to correspond to the definitions of LoA adopted.

The structure of the functional diagram (IDEF0) in Figure 3 is very similar to the automation system developed for this case study and illustrated in Figure 4. As Table 8 shows, different level of automation scores can be obtained using the AHP weight structure. Based on the influence of variability on specific

Table 7. Applied AHP results derived from taxonomy.

	Attribute	Output/Inputs			Strategy		Time		Requirements						
		Parameter	Quantity	Diversification	Interval of variability	Interdependency	Number of alternatives	Number of actions	Patterned actions	Concurrency	Time availability	Sensorial prerequisite	Cognitive prerequisite	Physical prerequisite	Total
Process	Weight		0.060	0.062	0.224	0.036	0.021	0.015	0.020	0.064	0.210	0.047	0.140	0.101	1.000
	Score (1–10)		8	5	10	10	10	5	5	10	10	5	5	10	8.46
Screw identification and location	Weighted score		0.48	0.31	2.24	0.36	0.21	0.07	0.10	0.64	2.10	0.23	0.70	1.01	
	Score (1–10)		5	5	10	10	8	5	5	10	10	5	5	10	8.24
Grasp and move screw to location	Weighted score		0.30	0.31	2.24	0.36	0.17	0.07	0.10	0.64	2.10	0.23	0.70	1.01	
	Score (1–10)		10	0	10	5	7	5	5	8	10	5	5	5	7.39
Align and insert	Weighted score		0.60	0.00	2.24	0.18	0.15	0.07	0.10	0.51	2.10	0.23	0.70	0.50	
	Score (1–10)		3	0	0	5	5	0	5	5	5	0	5	5	3.14
Fastening	Weighted score		0.18	0.00	0.00	0.18	0.11	0.00	0.10	0.32	1.05	0.00	0.70	0.50	
	Score (1–10)		10	10	10	5	9	10	10	5	5	5	10	10	8.19
	Weighted score		0.60	0.62	2.24	0.18	0.19	0.15	0.20	0.32	1.05	0.23	1.40	1.01	

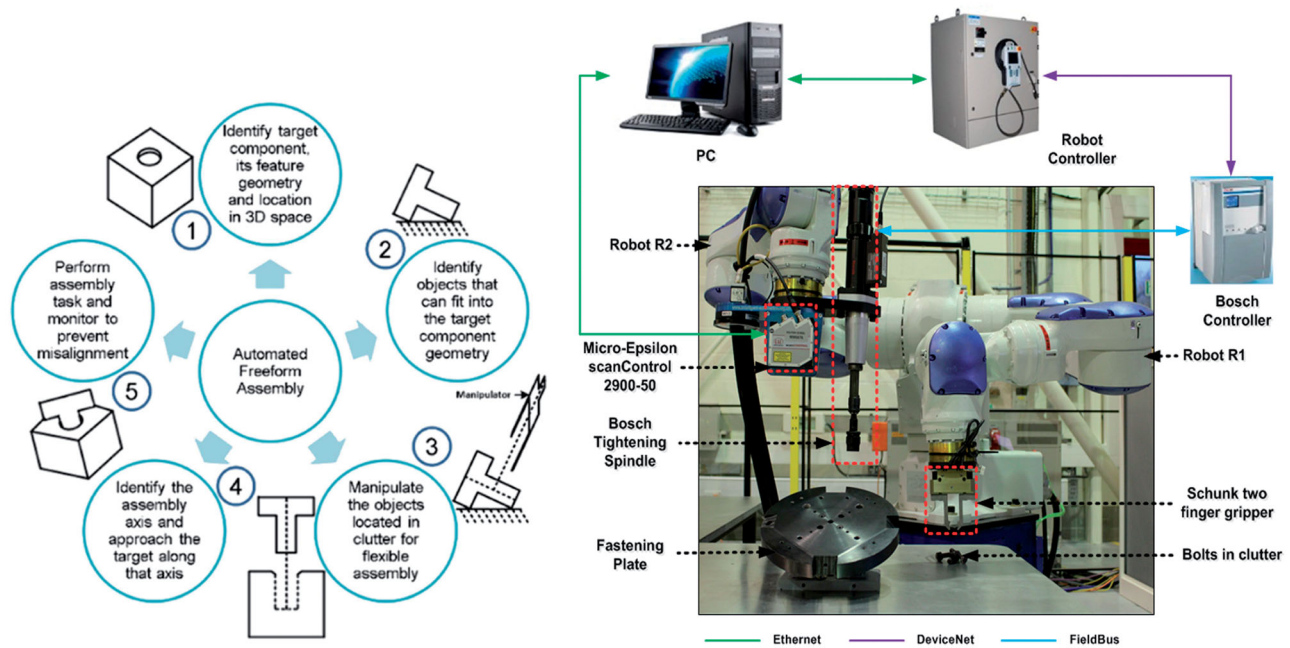


Figure 4. Process involved in automated non-structured assembly solution (Dharmara et al. 2018), licensed under <http://creativecommons.org/licenses/by/4.0/>.

Table 8. Summary of level of automation suggested for fastener assembly process.

Tasks	Level of automation suggested (Score out of 10)	Selected automation technology
Hole identification and location	Low level of automation (8.5)	Micro-Epsilon scan Control I 2900-50 laser profile scanner, point cloud feature detection
Screw identification and location	Low level of automation (8.2)	Micro-Epsilon scan Control, point cloud to CAD surface matching
Grasp and move screw to location	Low level of automation (7.4)	Schunk two finger gripper, Yaskawa Motoman
Align and insert	Moderate level of automation (3.1)	Schunk two finger gripper, Yaskawa Motoman
Fastening	Low level of automation (8.2)	Schunk two finger gripper, Bosch tightening spindle, Yaskawa Motoman

Note: The computing power was provided with an Intel Core i7 processor with 3.40-GHz speed.

parts of the systems design, different scores are calculated. The first three tasks are classified as suitable for the *low* level of automation, mainly due to time availability, which is limited by the time required to process point clouds for the vision system. The 'alignment and insert' task is rated as *moderate* based on the variability score. Similar findings can be found as a significant amount of research uses special insertion tasks in the field of control mechanism based on counterforce (see, for example, Zhao et al. 2016). The final fastening task also suits a *low* level of automation because of the intricacy in avoiding a cross-threading scenario in automation.

These results do concur with the current understanding of automation difficulty for the associated tasks. This recommendation is made to reduce automation complexity for tasks with high variability (human operators are preferred), however, a higher level of automation may be desired but at the expense of increased cost. The presented application of the taxonomy shows that it can add to the design knowledge for the automation system to overcome variabilities and identifies where automation may be difficult due to the variability of the tasks.

5. Conclusions

Variability is identified as a reason for a lack of robustness in production processes. With the current trend towards

industrial automation, understanding variability has a direct impact on the complexity and the cost of automation systems. It has been discussed in this article that in a manual process variability is dealt with by experienced operators. However, in automated systems more embedded intelligence and reasoning capability are required to address variabilities in complex tasks. Consequently, such intelligence levels will require higher levels of automation at a much higher cost.

In this article, the authors propose a variability taxonomy linked to the automation systems to facilitate decision making on a suitable level of automation based on the variabilities in the tasks. The novelty of this research lies in developing a variability taxonomy based on automation processes and technologies to be considered prior to decision making on automating systems.

The research reported in this article started by reviewing the existing literature and identifying a lack of understanding between process variability and the need for an adequate level of automation. The developed taxonomy was defined with a comprehensive set of attributes (e.g. input, strategy, time, and requirement) and their parameters (such as quantity, interval range, dependency, cognitive requisite). The IDEF modelling approach was used to formally construct the taxonomy. Three case studies on grinding, deburring, and welding processes were used to evaluate the effectiveness of the proposed taxonomy and to refine the proposed modelling method. To

validate the proposed approach, the proposed taxonomy was applied to an automated bolt fastening scenario, which was built based on existing manual fastening processes. A model was constructed based on the generic attributes and parameters, in addition to a series of automation levels and their associated automation technologies (and their vendors). The results of this exercise successfully identified appropriate levels of automation for each task, which were compatible with the actual automation system designed and developed by the experts. This case study proved that the use of the proposed taxonomy can facilitate the definition of appropriate levels of automation for complex tasks.

Further research is planned in two main areas. Initially, the proposed taxonomy is to be applied to various industrial scenarios to further investigate the effectiveness of the approach in different industries. Secondly, more comprehensive levels of automation are to be developed and linked to a series of structured automated technologies, independent from vendors. Such definition of technologies will then be linked to the IDEF models to facilitate an automated generation of technologies required for complex tasks and potentially a list of available vendors.

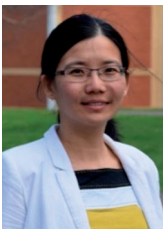
Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

The authors would like to acknowledge the support of the UK Engineering and Physical Sciences Research Council (EPSRC) Centre for Innovative Manufacturing in Intelligent Automation, in undertaking this research work under grant reference number [EP/I033467/1].

Notes on contributors



Yee Mey Goh received her BEng (Hons) in Mechanical Engineering from University Tenaga Nasional, Malaysia and PhD from University of Bristol, UK. She is currently a senior lecturer in Wolfson School of Mechanical, Electrical and Manufacturing Engineering at Loughborough University. Her interdisciplinary research addresses risk and uncertainty in early design of complex, novel and through-life systems, focussing on the

development of robust methodology and models to support complex multidisciplinary decision making. She is a member of the Design Society and serves as an Advisory Committee of The Consortium of UK University Manufacturing and Engineering for the Engineering Professors' Council.



Simon Micheler was awarded both his BSc and MSc degree in industrial engineering at the Ilmenau University of Technology, Germany in 2013 and 2015, respectively. His main fields of interest were supply chain management and production technology. He joined the Intelligent Automation Centre in January 2016 as a PhD student, where his research is

based on the business of automation and, more specifically, on the implementation of intelligent automation systems in manufacturing businesses.



Angel Sanchez-Salas is a project engineer in a manufacturing company in the recycling industry. He obtained his PhD in Mechanical and Manufacturing Engineering from Loughborough University (United Kingdom) and has extensive experience in manufacturing and automation in different sectors, including defence, aerospace and automotive. In addition, he collaborates as an expert reviewer for the Ontario Centers of Excellence (Canada). He was a Post-doctoral Fellow in the Cognitive Engineering Laboratory at the University of Toronto. Current research interests include business of automation, adaptive automation, manufacturing variability, sustainability, and flexible automation.



Keith Case, BSc, PhD, CEng, CITP, FErgs, FBCS is a Professor of Computer Aided Engineering in Mechanical, Electrical and Manufacturing Engineering at Loughborough University and is a Chartered Engineer, Fellow of the Ergonomics and Human Factors Society and a Fellow of the British Computer Society. He is also director of SAMMIE CAD Limited, a company that develops and markets the digital human modelling tool SAMMIE. In 1994,

he received the Ergonomics Society Otto Edholm Award in recognition of his significant contribution to the development and application of ergonomics, primarily in the area of digital human modelling. Current research interests include inclusive design, human aspects of automation, cognitive ergonomics in manufacturing assembly, the ageing workforce, human behavioural modelling, digital human modelling, knowledge-based design and manufacture, feature-based design and process planning.



Daniel P. Bumblauskas is an Associate Professor and the Hamilton/ESP International Fellow for Supply Chain and Logistics Management at the University of Northern Iowa College of Business. Dan also serves as a visiting professor at the University of Washington and holds a courtesy appointment at the University of Missouri where he previously held a faculty position. Dan has published over 40 peer-reviewed journal articles and conference proceedings, including publications in journals such as *Expert Systems with Applications*, *IEEE Transactions on Industry Applications* and *Business Process Management*. He earned a B.S. in Industrial Engineering and Economics from Iowa State University, a master of liberal arts in general management from Harvard University and received his M.S. and Ph.D., both from Iowa State University, in Industrial Engineering.

ings, including publications in journals such as *Expert Systems with Applications*, *IEEE Transactions on Industry Applications* and *Business Process Management*. He earned a B.S. in Industrial Engineering and Economics from Iowa State University, a master of liberal arts in general management from Harvard University and received his M.S. and Ph.D., both from Iowa State University, in Industrial Engineering.



Radmehr P. Monfared holds BSc degree in Mechanical Engineering, MSc in Computer Integrated Manufacturing and PhD in Modelling of Cell Control Systems (2000-Loughborough University). Worked for more than 17 years with various industrial domains, including automotive, aerospace, electronics, and train maintenance, with main focus on manufacturing automation, virtual engineering, production control and monitoring, and business analysis

and simulation.

References

- Antony, J., M. Hughes, and M. Kaye. 1999. "Reducing Manufacturing Process Variability Using Experimental Design Technique: A Case Study." *Integrated Manufacturing Systems* 10(3): 162–170. doi:10.1108/09576069910264420.
- Antony, J., M. Hughes, M. Kaye, J. Antony, and M. Hughes. 2000. "Reducing Manufacturing Process Variability Using Experimental Design Technique: A Case Study." *Integrated Manufacturing Systems* 10 (3): 162–170. doi:10.1108/09576069910264420.
- Apley, D. W., and J. Shi. 2001. "A Factor-Analysis Method for Diagnosing Variability in Multivariate Manufacturing Processes." *Technometrics* 43(1): 84–95. doi:10.1198/00401700152404354.
- Asare, S., and L. McDaniel. 1996. "The Effects of Familiarity with the Preparer and Task Complexity on the Effectiveness of the Audit Review Process." *The Accounting Review* 71(2): 139–159. doi:10.2308/bria.2007.19.1.1.
- Baccarini, D. 1996. "The Concept of Project Complexity—A Review." *International Journal of Project Management* 14(4): 201–204. doi:10.1016/0263-7863(95)00093-3.
- Bailey, N. R., and M. W. Scerbo. 2007. "Automation-Induced Complacency for Monitoring Highly Reliable Systems: The Role of Task Complexity, System Experience, and Operator Trust." *Theoretical Issues in Ergonomic Science* 8(4): 321–348. doi:10.1080/14639220500535301.
- Bell, D. J., and I. Ruthven. 2004. "Searcher's Assessments of Task Complexity for Web Searching." In *Advances in Information Retrieval*, edited by S. McDonald, J. Tait, ECIR 2004. Lecture Notes in Computer Science, Vol. 2997. 57–71. Berlin Heidelberg: Springer.
- Billings, C. 1997. *Aviation Automation: The Search for a Human-Centered Approach*. Mahwah, NJ: Lawrence Erlbaum Associates.
- Birkhofer, R., M. Wollschläger, R. Schrieber, M. Winzenick, J. Kalhoff, C. Kleedörfer, M. Mühlhause, and J. Niemann. 2010. Life-Cycle-Management Für Produkte Und Systeme Der Automation: ein Leitfaden des Arbeitskreises Systemaspekte im ZVEI Fachverband Automation. Zentralverb. Elektrotechnik- und Elektronikindustrie, Fachverb. Automation, 2010.
- Boag, C., A. Neal, S. Loft, and G. Halford. 2006. "An Analysis of Relational Complexity in an Air Traffic Control Conflict Detection Task." *Ergonomics* 49(14): 1508–1526. doi:10.1080/00140130600779744.
- Boff, K. R. 2006. "Revolutions and Shifting Paradigms in Human Factors and Ergonomics." *Applied Ergonomics* 37: 391–399.
- Bonner, S. E. 1994. "A Model of the Effects of Audit Task Complexity." *Accounting Organizations, and Society* 19(3): 213–234. doi:10.1016/0361-3682(94)90033-7.
- Burger, N., M. Demartini, F. Tonelli, F. Bodendorf, and C. Testa. 2017. "Investigating Flexibility as a Performance Dimension of a Manufacturing Value Modeling Methodology (MVMM): A Framework for Identifying Flexibility Types in Manufacturing Systems." *Procedia CIRP* 63: 33–38. doi:10.1016/j.procir.2017.03.343.
- Byrne, E. A., and R. Parasuraman. 1996. "Psychophysiology and Adaptive Automation." *Biological Psychology* 42(3): 249–268.
- Byström, K., and K. Järvelin. 1995. "Task Complexity Affects Information Seeking and Use." *Information Processing and Management* 31(2): 191–213. doi:10.1016/0306-4573(95)80035-R.
- Campbell, D. 1988. "Task Complexity: A Review and Analysis." *Academy of Management Review* 13(1): 40–52. doi:10.2307/258353.
- Campbell, D., and K. Gingrich. 1986. "The Interactive Effects of Task Complexity and Participation on Task Performance: A Field Experiment." *Organizational Behaviour and Human Decision Processes* 38(2): 162–180. doi:10.1016/0749-5978(86)90014-2.
- Carey, J., and C. Kacmar. 1997. "The Impact of Communication Mode and Task Complexity on Small Group Performance and Member Satisfaction." *Computers in Human Behaviour* 13(1): 23–49. doi:10.1016/S0747-5632(96)00027-1.
- Chan, F. T. S., M. H. Chan, H. Lau, and R. W. L. Ip. 2001. "Investment Appraisal Techniques for Advanced Manufacturing Technology (AMT): A Literature Review." *Integrated Manufacturing Systems* 12(1): 35–47. doi:10.1108/09576060110361528.
- Chmiel, N. 2008. *An Introduction to Work and Organizational Psychology: A European Perspective*. Chichester: John Wiley and Sons.
- Chmiel, N., F. Fraccaroli, and M. Sverke. 2017. *An Introduction to Work and Organizational Psychology: An International Perspective*. Hoboken, NJ: John Wiley and Sons.
- Dai, W., and J. Yang. 2011. "Decision-Making in Process Design Based on Failure Knowledge." 2011 IEEE International Conference on Industrial Engineering and Engineering Management, 1505–1509.
- de Winter, J. C. F., and D. Dodou. 2014. "Why the Fitts List Has Persisted throughout the History of Function Allocation." *Cognition, Technology and Work* 16(1): 1–11. doi:10.1007/s10111-011-0188-1.
- Demartini, M., F. Tonelli, L. Damiani, R. Revetria, and L. Cassettari. 2017. "Digitalization of Manufacturing Execution Systems: The Core Technology for Realizing Future Smart Factories." 22nd Summer School "Francesco Turco" – Industrial Systems Engineering 2017, Vol. 2017, September, 326–333.
- Dharmara, K., R. P. Monfared, P. S. Ogun, and M. R. Jackson. 2018. "Robotic Assembly of Threaded Fasteners in a Non-Structured Environment." *The International Journal of Advanced Manufacturing Technology* 98(5–8): 2093. doi:10.1007/s00170-018-2363-5.
- Dharmaraj, K. 2015. "Automated Freeform Assembly of Threaded Fasteners." PhD thesis, Loughborough: Loughborough University.
- Digiesi, S., A. Kock, G. Mummolo, and J. E. Rooda. 2009. "The Effect of Dynamic Worker Behavior on Flow Line Performance." *International Journal of Production Economics* 120(2): 368–377. doi:10.1016/j.ijpe.2008.12.012.
- Dixit, P. M., and U. S. Dixit. 2008. *Modeling of Metal Forming and Machining Processes: By Finite Element and Soft Computing Methods*. Springer Science and Business Media. London: Springer-Verlag.
- Dixon, S., and C. Wickens. 2006. "Reliability in Automated Aids for Unmanned Aerial Vehicle Flight Control: Evaluating a Model of Automation Dependence in High Workload." *Human Factors: The Journal of the Human Factors and Ergonomics Society* 48(3): 474–486. doi:10.1518/001872006778606822.
- Doerr, K. H., and A. Arreola-Risa. 2000. "A Worker-Based Approach for Modeling Variability in Task Completion Times." *IEE Transactions* 32(7): 625–636. doi:10.1080/07408170008967421.
- El-Khalil, R., and Z. Darwish. 2019. "Flexible Manufacturing Systems Performance in U.S. Automotive Manufacturing Plants: A Case Study." *Production Planning and Control* 30 (1): 48–59. doi:10.1080/09537287.2018.1520318.
- Fatorachian, H., and H. Kazemi. 2018. "A Critical Investigation of Industry 4.0 in Manufacturing: Theoretical Operationalisation Framework." *Production Planning and Control* 29(8): 633–644.
- Feigh, K. M., M. C. Dorneich, and C. C. Hayes. 2012. "Toward a Characterization of Adaptive Systems: A Framework for Researchers and System Designers." *Human Factors* 54(6): 1008–1024. doi:10.1177/0018720812443983.
- Fitts, P. M. 1951. *Human Engineering for an Effective Air-Navigation and Traffic-Control System*. Air Navigation Development Board. Oxford, England: National Research Council, Division of Anthropology and Psychology, Committee on Aviation Psychology.
- Foresight. 2013. *The Future of Manufacturing. A New Era of Opportunity and Challenge for the UK*. Project Report. London: The Government Office for Science.
- Frohm, J., V. Lindström, J. Stahre, and M. Winroth. 2008. "Levels of Automation in Manufacturing." *Ergonomics – An International Journal of Ergonomics and Human Factors* 30(3): 1–28.
- Gardner, D. 1990. "Task Complexity Effects on Non-Task-Related Movements: A Test of Activation Theory." *Organizational Behaviour and Human Decision Processes* 45(2): 209–231. doi:10.1016/0749-5978(90)90012-X.
- Glodek, M., et al. 2006. "Process Robustness." *Pharmaceutical Engineering (Online Exclusive)* 26(6): 1–11.
- Goodrich, M. A., and E. R. Boer. 2003. "Model-Based Human-Centered Task Automation: A Case Study in ACC System Design." *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans* 33(3): 325–336. doi:10.1109/TSMCA.2003.817040.
- Greitzer, F. L. 2005. "Toward the Development of Cognitive Task Difficulty Metrics to Support Intelligence Analysis Research." Fourth IEEE Conference on Cognitive Informatics, University of California, Irvine, USA, 315–320.

- Groover, M. P. 2007. *Automation, Production Systems and Computer-Integrated Manufacturing*. New Jersey, NJ: Prentice Hall Press.
- Gutenberg, R. L., R. D. Arvey, H. G. Osburn, and P. R. Jeanneret. 1983. "Moderating Effects of Decision-Making/Information-Processing Job Dimensions on Test Validities." *Journal of Applied Psychology* 68(4): 602–608. doi:10.1037/0021-9010.68.4.602.
- Ham, D., J. Park, and W. Jung. 2011. "A Framework-Based Approach to Identifying and Organizing the Complexity Factors of Human-System Interaction." *IEEE Systems Journal* 5(2): 213–222. doi:10.1109/JSYST.2010.2102574.
- Hartley, A. A., and J. W. Anderson. 1983. "Task Complexity and Problem-Solving Performance in Younger and Older Adults." *Journals Gerontol* 38(1): 72–77. doi:10.1093/geronj/38.1.72.
- Harvey, C. M., and R. J. Koubek. 2000. "Cognitive, Social, and Environmental Attributes of Distributed Engineering Collaboration: A Review and Proposed Model of Collaboration." *Human Factors and Ergonomics in Manufacturing* 10(4): 369–393.
- Hendy, K. C., J. Liao, and P. Milgram. 1997. "Combining Time and Intensity Effects in Assessing Operator Information-Processing Load." *Human Factors: The Journal of the Human Factors and Ergonomics Society* 39(1): 30–47. doi:10.1518/001872097778940597.
- Herrmann, J. 2015. *Engineering Decision Making and Risk Management*. 1st ed. Hoboken, NJ, New York: Wiley.
- Ho, T. H., and K. Weigelt. 1996. "Task Complexity, Equilibrium Selection, and Learning: An Experimental Study." *Management Science* 42(5): 659–679. doi:10.1287/mnsc.42.5.659.
- Jamshidi, J., A. Kayani, P. Irvani, P. G. Maropoulos, and M. D. Summers. 2009. "Manufacturing and Assembly Automation by Integrated Metrology Systems for Aircraft Wing Fabrication." *Proceedings of the Institution of Mechanical Engineers Part B Journal of Engineering Manufacture* 224(1): 25–36. doi:10.1243/09544054JEM1280.
- Kihlman, H. 2005. *Affordable Automation for Airframe Assembly: Developing of Key Enabling Technologies*. Linköping, Sweden: Linköping University Electronic Press.
- Kim, C., and M. Khoury. 1987. "Task Complexity and Contingent Information Processing in the Case of Couple's Decision Making." *Journal of the Academy of Marketing Science* 15(3): 32–43. doi:10.1177/009207038701500304.
- Klein, G. 1993. "Sources of Error in Naturalistic Decision Making Tasks." In *Proceedings of the Human Factors and Ergonomics Society 37th Annual Meeting*, Seattle, Washington, 368–371. doi:10.1177/154193129303700424.
- Levinthal, B. R., and C. D. Wickens. 2006. "Management of Multiple Uavs with Imperfect Automation." Vol. 50. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, San Francisco, California, 1941–1944. doi:10.1177/154193120605001748.
- Liu, P., and Z. Li. 2012. "Task Complexity: A Review and Conceptualization Framework." *International Journal of Industrial Ergonomics* 42(6): 553–568. doi:10.1016/j.ergon.2012.09.001.
- Lohse, G. L. 1997. "The Role of Working Memory on Graphical Information Processing." *Behaviour and Information Technology* 16(6): 297–308. doi:10.1080/014492997119707.
- Lohse, N., H. Hirani, S. Ratchev, and M. Turitto. 2005. "An Ontology for the Definition and Validation of Assembly Processes for Evolvable Assembly Systems." *Proceedings of IEEE International Symposium on Assembly and Task Planning* 2005: 242–247.
- Loose, J., S. Zhou, and D. Ceglarek. 2019. "Variation Source Identification in Manufacturing Processes Based on Relational Measurements of Key Product Characteristics." *Journal of Manufacturing Science and Engineering* 130(3): 031007 (1–11).
- Lorenz, B., F. D. Nocera, S. Röttger, and R. Parasuraman. 2002. "Automated Fault-Management in a Simulated Spaceflight Micro-World." *Aviation, Space, and Environmental Medicine* 73(9): 886–897.
- Madsen, E. S., and L. L. Mikkelsen. 2018. "The Need for Knowledge Modification in Technology Change: A Framework to Consider Changes in Domain Complexity, Knowledge and Productivity." *Production and Planning Control* 29(2): 91–105. doi:10.1080/09537287.2017.1373872.
- Manorathna, P., S. Marimuthu, L. Justham, and M. Jackson. 2017. "Human Behaviour Capturing in Manual Tungsten Inert Gas Welding for Intelligent Automation." *Proceedings of the Institution of Mechanical Engineers, Part B, Journal of Engineering Manufacture* 231(9): 1619–1627. doi:10.1177/0954405415604313.
- Mantripragada, R., and D. Whitney. 1999. "Modeling and Controlling Variation Propagation in Mechanical Assemblies." *IEEE Transactions on Robotics and Automation* 15(1): 124–140. doi:10.1109/70.744608.
- Manyika, J., M. Chui, M. Miremadi, J. Bughin, K. George, P. Willmott, and M. Dewhurst. 2017. *A Future That Works: Automation, Employment, and Productivity*, 1–28. Chicago: McKinsey Global Institute.
- Manzey, D., J. Reichenbach, and L. Onnasch. 2008. "Performance Consequences of Automated Aids in Supervisory Control: The Impact of Function Allocation." *Human Factors and Ergonomics Society Annual Meeting* 52(4): 297–301. doi:10.1177/154193120805200421.
- Marshall, T. E., and T. A. Byrd. 1998. "Perceived Task Complexity as a Criterion for Information Support." *Information and Management* 34(5): 251–263. doi:10.1016/S0378-7206(98)00057-3.
- Mascha, M., and C. Miller. 2010. "The Effects of Task Complexity and Skill on over/under-Estimation of Internal Control." *Managerial Auditing Journal* 25(8): 734–755. doi:10.1108/02686901011069533.
- Molloy, R., and R. Parasuraman. 1996. "Monitoring an Automated System for a Single Failure: Vigilance and Task Complexity Effects." *Human Factors: The Journal of the Human Factors and Ergonomics Society* 38(2): 311–322. doi:10.1177/001872089606380211.
- Montgomery, D. C., C. L. Jennings, and M. Kulahci. 2008. *Introduction to Time Series Analysis and Forecasting*. Hoboken, NJ: John Wiley & Sons Inc.
- Mosier, K. L., N. Sethi, S. McCauley, L. Khoo, and J. M. Orasanu. 2007. "What You Don't Know Can Hurt You: Factors Impacting Diagnosis in the Automated Cockpit." *Human Factors: The Journal of the Human Factors and Ergonomics Society* 49(2): 300–310. doi:10.1518/001872007X312513.
- Nadkarni, S., and R. Gupta. 2007. "A Task-Based Model of Perceived Website Complexity." *MIS Quarterly Management Information Systems* 31(3): 501–524.
- National Institute of Standards and Technology (NIST/SEMATECH). 2016. "e-Handbook of Statistical Methods." Accessed 9 July 2019. <http://www.itl.nist.gov/div898/handbook/>
- O'Donnell, E., and E. N. Johnson. 2001. "The Effects of Auditor Gender and Task Complexity on Information Processing Efficiency." *International Journal of Auditing* 5(2): 91–105. doi:10.1111/j.1099-1123.2001.00328.x.
- Parasuraman, R., T. B. Sheridan, and C. D. Wickens. 2000. "A Model for Types and Levels of Human Interaction with Automation." *IEEE Transactions on Systems, Man, and Cybernetics. Part A, Systems and Humans: A Publication of the IEEE Systems, Man, and Cybernetics Society* 30(3): 286–297.
- Park, S. H., and J. C. Woldstad. 2000. "Multiple Two-Dimensional Displays as an Alternative to Three-Dimensional Displays in Telerobotic Tasks." *Human Factors: The Journal of the Human Factors and Ergonomics Society* 42(4): 592–603. doi:10.1518/001872000779698060.
- Payne, J. W. 1976. "Task Complexity and Contingent Processing in Decision Making: An Information Search and Protocol Analysis." *Organizational Behaviour and Human Performance* 16(2): 366–387. doi:10.1016/0030-5073(76)90022-2.
- Payne, J. W., J. R. Bettman, and E. J. Johnson. 1992. "Behavioral Decision Research: A Constructive Processing Perspective." *Annual Review of Psychology* 43(1): 87–131. doi:10.1146/annurev.ps.43.020192.000511.
- Piggin, R. 2005. "Developments in Industrial Robotic Safety." *Industrial Robot: An International Journal* 32(4): 303–311. doi:10.1108/01439910510600146.
- Rawat, P., K. D. Singh, H. Chaouchi, and J. M. Bonnin. 2014. "Wireless Sensor Networks: A Survey on Recent Developments and Potential Synergies." *The Journal of Supercomputing* 68(1): 1–48. doi:10.1007/s11227-013-1021-9.
- Reichenbach, J., L. Onnasch, and D. Manzey. 2011. "Human Performance Consequences of Automated Decision Aid in States of fatigue." *Human Factors: The Journal of the Human Factors and Ergonomics Society* 53(6): 717–728. doi:10.1177/0018720811418222.
- Röttger, S., K. Bali, and D. Manzey. 2009. "Impact of Automated Decision Aids on Performance, Operator Behaviour and Workload in a

- Simulated Supervisory Control Task." *Ergonomics* 52(5): 512–523. doi:10.1080/00140130802379129.
- Rouse, W. B., and S. H. Rouse. 1979. "Measures of Complexity of Fault Diagnosis Tasks." *IEEE Transactions on Systems, Man and Cybernetics* 9(11): 720–727.
- Rovira, E., K. McGarry, and R. Parasuraman. 2007. "Effects of Imperfect Automation on Decision Making in a Simulated Command and Control Task." *Human Factors: The Journal of the Human Factors and Ergonomics Society* 49(1): 76–87. doi:10.1518/001872007779598082.
- Saaty, T. L. 1990. "How to Make a Decision: The Analytic Hierarchy Process." *European Journal of Operational Research*. 48(1): 9–26. doi:10.1016/0377-2217(90)90057-1.
- Sanchez-Salas, A. 2016. "A Framework to Support Automation in Manufacturing through the Study of Process Variability." PhD thesis, Loughborough: Loughborough University.
- Sandom, C., and R. Harvey. 2004. *Human Factors for Engineers*. London: Institution of Electrical Engineers.
- Satchell, P. 1998. *Innovation and Automation*. London: Ashgate.
- Sauer, J., P. Nickel, and D. Wastell. 2013. "Designing Automation for Complex Work Environments Under Different Levels of Stress." *Applied Ergonomics* 44(1): 119–127. doi:10.1016/j.apergo.2012.05.008.
- Schwab, D. P., and L. L. Cummings. 1976. "A Theoretical Analysis of the Impact of Task Scope on Employee Performance." *Academy of Management Review* 1(2): 23–25. doi:10.5465/amr.1976.4408660.
- Schwarzwald, J., M. Koslowsky, and T. Ochana-Levin. 2003. "Usage of and Compliance with Power Tactics in Routine versus Nonroutine Work Settings." *Journal of Business and Psychology* 18(3): 385–402. doi:10.1023/B:JOB0.0000016713.86935.1b.
- Simnett, R. 1996. "The Effect of Information Selection, Information Processing and Task Complexity on Predictive Accuracy of Auditors." *Accounting, Organizations and Society* 21(7–8): 699–719. doi:10.1016/0361-3682(96)00006-2.
- Sintchenko, V., and E. Coiera. 2003. "Which Clinical Decisions Benefit from Automation. A Task Complexity Approach." *International Journal of Medical Informatics* 70(2–3): 309–316. doi:10.1016/S1386-5056(03)00040-6.
- Skjerve, A. B., and A. Bye. 2011. *Simulator-Based Human Factors Studies Across 25 Years*. London: Springer.
- Speier, C. 2006. "The Influence of Information Presentation Formats on Complex Task Decision-Making Performance." *International Journal of Human-Computer Studies* 64(11): 1115–1131. doi:10.1016/j.ijhcs.2006.06.007.
- Steinmann, D. O. 1976. "The Effects of Cognitive Feedback and Task Complexity in Multiple-Cue Probability Learning." *Organizational Behaviour and Human Performance* 15(2): 168–179. doi:10.1016/0030-5073(76)90035-0.
- Svenson, O., and A. Edland. 1987. "Change of Preferences under Time Pressure: Choices and Judgements." *Scandinavian Journal of Psychology* 28(4): 322–330. doi:10.1111/j.1467-9450.1987.tb00769.x.
- Thornton, A. 1999. "Variation Risk Management Using Modelling and Simulation." *Journal of Mechanical Design* 121(2): 297–304. doi:10.1115/1.2829457.
- Thornton, A., S. Donnelly, and B. Ertan. 2000. "More than Just Robust Design: Why Product Development Organizations Still Contend with Variation and Its Impact on Quality." *Research in Engineering Design* 12(3): 127–143. doi:10.1007/s001630050028.
- U.S. Department of Commerce. 1993. *FIPS PUB 183: Integration Definition for Function Modeling (IDEF0)*. National Institute of Standards and Technology, 120. Washington: U.S. Government Printing Office.
- Venter, H. S., and J. H. P. Eloff. 2003. "A Taxonomy for Information Security Technologies." *Computers and Security* 22(4): 299–307. doi:10.1016/S0167-4048(03)00406-1.
- Wang, H., M. Lewis, P. Velagapudi, P. Scerri, and K. Sycara. 2009. "How Search and Its Subtasks Scale in N Robots." Proceedings of the 4th ACM/IEEE international conference on Human robot interaction, San Antonio, TX, 141.
- Wang, H., S. Y. Chien, M. Lewis, P. Velagapudi, P. Scerri, and K. Sycara. 2009. "Human teams for Large Scale Multirobot Control." Conference Proceedings – IEEE International Conference on Systems, Man and Cybernetics, San Antonio, TX, 1269–1274.
- Wang, L., G. Jamieson, and J. G. Hollands. 2009. "Trust and Reliance on an Automated Combat Identification System." *Human Factors: The Journal of the Human Factors and Ergonomics Society* 51(3): 281–291. doi:10.1177/0018720809338842.
- Wang, Q., M. Sowden, and A. Mileham. 2013. "Modelling Human Performance within an Automotive Engine Assembly Line." *The International Journal of Advanced Manufacturing Technology* 68(1–4): 141–148. doi:10.1007/s00170-012-4714-y.
- Williams, T. J., and H. Li. 1999. "PERA and GERAM—Enterprise Reference Architectures in Enterprise Integration." In: *Information Infrastructure Systems for Manufacturing II*. DIISM 1998. edited by J.J. Mills, F. Kimura. Vol. 16. IFIP — The International Federation for Information Processing, Boston, MA: Springer.
- Williams, T. M. 1999. "The Need for New Paradigms for Complex Projects." *International Journal of Project Management* 17(5): 269–273. doi:10.1016/S0263-7863(98)00047-7.
- Wood, R. E. 1986. "Task Complexity: Definition of the Construct." *Organizational Behaviour and Human Decision Processes* 37(1): 60–82. doi:10.1016/0749-5978(86)90044-0.
- Xiao, Y., W. Hunter, C. Mackenzie, N. Jefferies, and R. Horst. 1996. "Task Complexity in Emergency Medical Care and Its Implications for Team coordination. LOTAS Group. Level One Trauma Anesthesia Simulation." *Human Factors* 38(4): 636–645. doi:10.1518/001872096778827206.
- Xu, S., Z. Li, F. Song, W. Luo, Q. Zhao, and G. Salvendy. 2009. "Influence of Step Complexity and Presentation Style on Step Performance of Computerized Emergency Operating Procedures." *Reliability Engineering and System Safety* 94(2): 670–674. doi:10.1016/j.res.2008.07.001.
- Zeller, B., C. Achtenhagen, and S. Föst. 2010. *Internet Der Dinge in Der Industriellen Produktion*. Nuremberg, Germany: Forschungsinstitut Betriebliche Bildung.
- Zhang, Y., Z. Li, B. Wu, and S. Wu. 2009. "A Spaceflight Operation Complexity Measure and Its Experimental Validation." *International Journal of Industrial Ergonomics* 39(5): 756–765. doi:10.1016/j.ergon.2009.03.003.
- Zhao, Y. C., Y. M. Goh, L. Justham, N. Lohse, and M. R. Jackson. 2016. "Human Skill Capture: A Hidden Markov Model of Force and Torque Data in Peg-in-a-Hole Assembly Process," In 2016 IEEE International Conference on Systems, Man, and Cybernetics, Budapest, Hungary, 655–660.
- Zheng, L. Y., C. A. McMahon, L. Li, L. Ding, and J. Jamshidi. 2008. "Key Characteristics Management in Product Lifecycle Management: A Survey of Methodologies and Practices." *Journal of Engineering Manufacture, Proceedings of the Institution of Mechanical Engineers Part B* 222(8): 989–1008. doi:10.1243/09544054JEM1045.