Describing Human-Automation Interaction in Production

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ABSTRACT

Although 'Human-Automation Interaction' (HAI) research has been approached from many areas there is no consensus of what effects interaction has in production systems. The role of interaction, especially in mixed automation, is important in order to better introduce new technology and to increase production rate and quality. Central concepts were studied in recent literature and three key-categories were found: *Human, Automation* and *Interaction centred.* The most frequent concepts *Levels of Automation, Trust and reliability* and *Automation use* were used to exemplify that interaction can be described using at least one concepts from each of the key-categories. It was seen that the usefulness of automation plays an important role in interaction and that interaction studies should include individual and perceived experiences.

Keywords: Human-Automation Interaction, Levels of Automation, Trust, Automation use, Literature review

1. INTRODUCTION AND PROBLEM AREA

Human-Automation Interaction (HAI) can be defined as the way a human is *affected by*, *controls* and *receives information* from automation while performing a task [1]. An example of this can be an operator in final assembly, using an automatic tool to mount a generator on an engine. The operator is *affected* by how the tool is constructed, by for instance its weight. He or she *controls* the tool and is given *information* in terms of vibration and for instance a pre-set draw while performing the task.

Manufacturing companies face a challenge in understanding and measuring interactions in order to become competitive. There are at least three important parts of this: studying how humans cooperate with new technology, understanding what competencies are needed and handling and reducing complexity within the work environment. In addition, there are high demands on flexible workstations, which means that there are many different types of tools on the same station. In addition there is often a flexible working team on that station who need to handle rapid changes in material and product variants. This means that there are many variables that affect HAI in production.

Although HAI has been approached from many perspectives the effects of interaction are still hard to predict [2-8]. Reasons for why interaction breakdowns occur have been attributed to a variety of different aspects, for instance: awareness and situational awareness [7, 9], performance [10, 11], feedback [9, 12] and Levels of Automation [10, 11, 13].
Recent literature points towards a need for finding quantifiable models [4, 14, 15] and to understand human behaviour, and the relationship between humans and automation [4, 16, 17].

If interaction between humans and automation can be described, modelled and measured, production performance can be improved in terms of reduced task time and error handling while maintaining product quality.

This paper examines how HAI can be described from a production perspective. The aim is to identify the most central concepts in recent HAI research, and to investigate how they can be used to understand interaction in production setting. The research question is:
What key- and sub-categories can be used to describe Human-Automation Interaction in a production context?

2. METHOD

Grounded Theory is used to develop a set of categories that through theory and literature can explain a phenomenon [18]. These categories include concepts that are kept provisional and earn its way to be incorporated in the category after being repeatedly seen in the data. The categories are formed iteratively were key-categories have a higher level and includes concepts from sub-categories (not all sub-categories will become categories).
Each raw data is coded i.e. given conceptualizations, so that they are easier to work with.
The significance of the method depends on the quality of the data i.e. scientific literature, the researchers analytic skills (when coding) as well as the sensitivity of using the theory and the action of forming and finding relation between categories. The coding and the first step of forming categories was done by the main author alone; which could provide some bias to the selection of papers. The other parts of the study which included forming and naming key-categories, finding and discussing the relation between them was done in cooperation with the other authors. The usefulness of the categories is discussed using a scenario example.

3. RESULTS

A literature review was based on parts of the Grounded Theory (GT) methodology i.e. categories and relations between the categories and their sub-categories [18]. 27 scientific papers, written between 2000 and 2011 were selected searching for the keywords "Human-Automation Interaction" and "Human-Automation Interaction and Production". Since HAI research has a long history, which is partly based on control-rooms and aviation, only papers from 2000 and forward were selected (in order to study recent central concepts). Papers that regard areas, which cannot be applied to a production context, were not included in the study.

The databases used to collect the papers were Academy of Computing Machinery (ACM), Institute of Electronical and Electronics Engineers (IEEE) and SpringerLink. In addition, some papers were found through reference lists of the cited papers. A complete list of the reviewed papers can be found in Appendix (Table A2).

The coding was done so that each paper could have one or more *central concepts*. This meant that the central aspect/concept or parameters in a paper were coded. The concepts were found studying abstracts, title, keywords and to some extent the body text of the papers. For instance if a focus concept of a paper was Levels of Automation, Levels of Automation this was coded as a central concept. In addition if another central concept was brought up in the paper like for instance changes in a system that too was included in the study.

3.1 Three key-categories: Human, Automation and Interaction centred

By studying the central concepts in recent literature three key-categories were formed: ***Human centred*** (N = 33), ***Automation centred*** (N = 32) and ***Interaction centred*** (N = 25), the categorization is seen in Figure 1 (See Appendix for references and a full categorization).

The Interaction centred key-category was differentiated first from the others since the concepts in that category included joint aspects (humans and automation), which was seen important in recent literature [4, 16, 17]). After this the human and automation centred categories were formed based on that they included concepts from the Human Factor and Production System area respectively.

Sub-categories for describing HAI were selected by looking at frequency where the presented sub-categories are those that represent >10% of the key-category.

The Human centred category incorporates concepts used to study or describe human factors. The most frequent sub-categories in this category are *Trust/reliability (N = 10)* and *Workload (N = 3).* This that point towards a different scope than previously seen in reviews and literature (see for instance [1] and [19]). Other concepts were self-confidence, safety, situational awareness, social reliance, attention and decision-making. From a production perspective the human factors are important and have been studied in terms of ergonomics.

The Automation centred category was formed since it represents performance indicators used to describe automation systems for instance performance, error/failure management, cost/economy, changes etc. From a production perspective factors connected to performance and automation are very important since they represent the way the system is described in terms of its productivity, efficiency and flexibility. The most frequent sub-categories were *Levels of Automation (N = 13), Performance (N = 4)* and *Changes (N = 4)*.

The Interaction centred category represents concepts that are connected to the joint system of human-automation. The most frequent sub-categories were *Automation use (N = 6), Adaptation (N = 4)* and *Communication (N = 3)*. Other concepts were support

	Human Centered N=33	
Trust and reliability N=10 [4, 6, 15-16, 26-29, 31, 36]	Workload N=3 [24, 26, 40]	
	Automation Centered N=32	
Levels of Automation N=9 [3, 14, 23-24, 26-27, 30, 32, 43]	Performance N=4 [4, 24, 27, 36]	Changes N=4 [19, 31, 36-37]
	Interaction Centered N=25	
Automation use N=6 [3-4, 6, 24, 27, 29]	Adaptation N=4 [3, 26, 31, 36]	Communication N=3 [15, 19, 43]

Figure 1: Categorization of Human-Automation Interaction

and aids, team performance, automation bias, coordination etc.

Studying the focus of the concepts included in the categories it is possible to see the differences between the categories. The ***Human centred*** concepts have a focus on the human and its emotions and perceptions while the ***Automation centred*** concepts focus on the automation and system description. The ***Interaction centred*** concepts focus instead on both on human and automation factors as a joint system. The relationships between them are exemplified in the next chapter.

3.2 The most frequent sub-categories: Levels of Automation, Trust and reliability and Automation use

From a production point of view, studying an example can help investigate the use of the categories and their relations. The sub-categories chosen are: *Levels of Automation (N = 12), Trust and reliability (N = 10)* and *Automation use (N = 6) (*light grey in Figure 1*)* where each of the sub-categories represents the most frequent concept from each of the key-categories. In this chapter literature from the review is combined with research from the production field.

The following scenario will be considered when exemplifying the sub-categories: a mixed automation assembly where automation and humans work in a joint system. The goal is to describe the HAI in a way that enables better insight of the interaction and interaction breakdowns connected to that HAI.
Levels of Automation justifies how the automation is characterized (*Automation centred*), *Trust and reliability* show the human perspective (*Human centred*) and *Automation use* represents human and automation measured in conjunction (*Interaction centred*).

Levels of Automation: It is important to study how *Levels of Automation (LoA)* can be seen as a discrete event instead of just an all-or-none process [3]. This can be used to describe a task in a more detailed way [14]. However there are complications to this since the levels and stages of *LoA* are becoming more complex.

Different scales have been used for defining LoA and a list of suggested scales was presented in Fasth et al. [20]. Included in that list was Frohm's definition of *LoA* as *"The allocation of physical and cognitive tasks between humans and technology as a continuum ranging from totally manual to totally automatic"* [21]. Frohm:s definition included two scales with seven increments ranging from manual work to totally automatic work. Fasth et al. developed a method, DYNAMO++ that included a matrix where physical and cognitive automation could be jointly described; the *LoA*-matrix is presented in Figure 2. DYNAMO++ has been used to suggest quality and performance improvements for assembly systems [22].

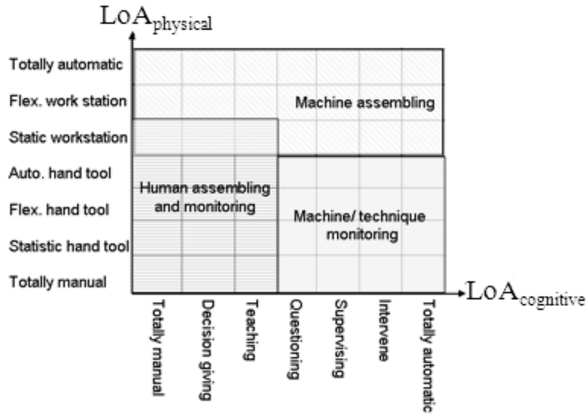

Figure 2: LoA-matrix showing joint physical and cognitive automation [22]

Here the *LoA*-matrix can serve as an objective tool to categorize automation in production.
A similar model was suggested by Parasaruman et al:s (definition of types and levels of automation). Two scales were suggested, with the first being similar to the *LoA* physical scale suggested by Fasth in Figure 2. However, the scale suggested by Parasaruman et al. has ten steps instead of seven. This scale was connected to the output of the system. The other scale was connected to the input of the system and the information processing, described in four stages. The Fasth matrix, on the other hand, describes one single state used to define at any given moment whether a task is performed by the human or by the automation (physical). This is relative to how much the human controls or has responsibility for the task (cognitive). Parasaruman et al:s model shows a system's automation level in conjunction to four mental states: information acquisition, information analysis, decision and action selection and finally action implementation. Fereidunian et al. [23], tested Parasarumans two-scaled definition, and stated that the two scales might be interdependent for same cases but not always. Fereidunian found that the model could explain tasks that have the suggested four stages and that it could be the same for tasks that involve un-manned operations. However he stated that the two scales might instead depend on one another when it comes to a whole task that has an integrated system. Miller et al. together with Parasaruman later suggested a further development of *LoA* where the affects of the HAI relationship could be seen as a trade-off between competency, mental workload and unpredictability. This was done in the context of air traffic control and task allocation, but can be regarded as useful in the understanding of automation use.
Miller et al. [24] stated that *LoA* is a combination of the roles and responsibilities between humans and automation i.e. an intermediate model. This is also true for the Fasth model. The use of an intermediated *LoA* was supported by Endsley et al. who noted that *LoA* could be used to improve system performance [10].

By using Parasaruman:s or Fasth:s definition of *LoA* it is possible to further describe HAI to better understand and predict breakdowns in interaction. In Mattsson et al. [25], *LoA* (according to Fasth), was used together with time to define and categorize interactions in an industrial case. This was used to find bottlenecks connected to specific tools, which indicated that cycle time could be reduced by introducing for instance training or appropriate support tools i.e. to find more detailed LoA solutions.

In the scenario with the mixed-model assembly *LoA* can be used to divide tasks into more detail enabling analysis for finding better and more detailed *LoA* solutions.

Relation between Levels of Automation and Trust and reliability: Parasuraman et al. defines trust as: *"A cognitive state that usually influences the actual, behavioral dependence on automation. "* [26], page 514. This means that *trust and reliability* is connected to LoA. Galster et al, states that it is important to investigate how *reliability* in *LoA* affects overall system performance [16].

In the scenario *trust* can be investigated from a subjective perspective in accordance to *LoA* to see if there are any specific tools that are not trusted.

Trust and reliability: The relation between *trust and reliability* is described by Cuevas et al. [15]. Cuevas et al:s theoretical view of team cognition includes *trust and reliability* which are described in relation to pre- and post-processes in HAI [15]. Here, *trust* is part of the pre-process, which is connected to the operators' beliefs and previous experience with automation. It is also connected to pre-task training that makes up part of the initial *trust* in automation. The post-process HAI includes feedback on performance regarding *reliability* and accuracy of the joint system (i.e. both the operator and automation). This information updates the operators' mental model of the joint system as well as calibrates the operator's *trust* in automation.

Merritt et al. studied two other types of *trust*, also connected to pre- and post-process: dispositional *trus*t and history-based *trust* [6]. Dispositional *trust* implies that the personal trait of being more likely to *trust* other people may make a person more likely to *trust* a non-human. History-based *trust* is connected to past interactions with a machine. As the usage is increased, history-based *trust* is more influenced by machine characteristics and less by dispositional trust (Ibid.).

Trust and reliability can be measured by subjective ratings and observation. Here the relation between *trust, reliability*, dispositional and history based trust might be useful in understanding why breakdowns in interaction occur.

Relation between Trust and reliability and Automation use: Merritt et al. state that generally research supports that people *use* machines less if they don't *trust* them and that automation errors affect *trust* negatively [6]. It was also seen that automation *reliability* affected automation more than workload demands did [27].

One important aspect is to study if an appropriate *trust* in automation can be found [28]. Lee states that understanding disuse and misuse might be connected to over-trust and under-trust. Disuse means that automation is not *used* even though it would increase system performance. Often a the misuse of automation is connected to that operators *use automation* in a way that was not intended by the designer [4]. Joachim Meyer however argue in Bustamante et al. [3] that it is hard to understand how and why automation is being *used*. Even though a source is trusted it may not be *used*, depending on individual preferences.

One way to solve this is to study user perception which can predict *automation use* [6]. Merritt state that researchers should use the perceived picture of machines, in addition to machine characteristics, in order to predict *automation use*. It was seen that when machine characteristics were kept the same it was seen that individual aspects affected perceived *trust* by 52% [6]. Hence it is important to investigate what individual differences that contribute to why the same machine may be perceived differently.

If *automation use* is studied objectively it can be compared to the subjective ratings hence providing more insight into for instance why a tool is used less. This way mis- and disuse might be studied. In addition the individual and perceived view of why a tool is not used can be important.

Automation use: The goal of finding an appropriate *LoA* or understanding a system is connected to finding the *usefulness* of it. Automation use can be described as when operators engage automation in order to perform tasks they would otherwise perform manually [4].

Some models of *automation use* are presented. The *use of automation* is, according to Lee et al., dependent on workload, cognitive overhead, trust, self-confidence and risk [4]. Miller et al. suggests that a mixture between human and automation is desirable where both parties should share control and efficiency. Aspects that are important regarding humans and automation are *competency, human workload* and *unpredictability* [24]. Competency is connected to that the system provides a correct response to a context. Human *workload* is connected to the cognitive energy that is used to run the system, and *unpredictability* means how hard the system is to predict. Connecting automation use to supportive tools, Johnson et al. claim that there are many complex factors that can affect usability, performance, confidence and safety [29].

Automation use is described above using different models. Common aspects are workload [4, 24, 27], *trust/perceived reliability* and self-confidence [4, 27]. Individual experience or preference were also seen as important [3, 6]. Since they cover a vast variety of factors it might be possible to quantify automation use by studying for instance *trust* or *LoA* instead. Furthermore, *automation use* can be measured in time or by subjective ratings.

Automation use and Levels of Automation: Sanchez presented a conceptual model of *automation use* [27].

In the model *automation use* is positively affected by workload, cost of concurrent task and perceived *reliability*. *Automation use* was negatively affected by probability of automation failure, self-confidence, cost of automated tasks and both positively and negatively affected by *LoA* and strategies of individual differences in *automation use*.

The parameters described can be either studied in an experiment lab or investigated indirectly by using subjective ratings, observation or interviews.

4. DISCUSSION

By using Grounded Theory it is possible to find sub- and key-categories that can describe a phenomenon. Since the aspects used to describe HAI are many, it is important to investigate how HAI can be quantified from a production perspective. The key-categories found were *Human, Automation and Interaction centred*. This includes concepts connected to human factors, the automation and system characteristics and the joint-system respectively.

The use and measurability of this conceptualization was exemplified by investigating how the sub-categories *Levels of Automation, Trust and reliability* and *Automation use* can describe HAI in production. And it was seen that all concepts can be connected to one another and that understanding interaction and its breakdowns is indeed complex. However, by studying the concepts separately and then in relation to one another, it is possible to at least determine where to start. The use of these three sub-categories is one way to describe the interaction between humans and automation in a production context, but it is by no means the only way. It is suggested that at least one concept from each of the key-categories should be used in order to describe HAI in production. In order to reduce bias effects seen in the study, only the main author was part of the first categorization and selection of papers, the concepts should be tested in a case study.

By studying the suggested concepts it appears that interaction can be divided into smaller parts by using *LoA,* which can be a first step of investigated the relationship between automation and humans in the HAI. By studying *Trust and reliability* it is possible to investigate whether the interaction breakdowns are connected to some type of *trust* issue. And there were some examples of types of trust that could be studied further. *Automation use* could be studied by testing one of the models presented or by using subjective or time measures connected to the common found parameters workload and self-confidence.

In addition it was found important to take individual and perceived experiences into account. Some suggestions on how to measure interaction were made including *LoA*, objective time measures, interviews and different types of subjective ratings. Future research includes deriving hypothesis based on the findings and testing the impact of sub-categories connected to the found key-categories.

From an industrial point of view, measuring and understanding interaction is crucial in order to optimize system performance and to stay competitive. By studying *usability* of the automation in connection to trust, for instance, it could be possible to predict and avoid interaction breakdowns. This can be studied when introducing new technologies or to understand competencies needed in production. This could also be investigated when handling complexity issues. Indirectly both competence and how people cope with complexity can be connected to *automation use* and *trust*, since if you are not accustomed to a specific automation you will *use* it and also *trust* it less. Training or finding appropriate support could be one key to reduce or hinder breakdowns.

5. CONCLUSIONS

The aim of this paper was to find what key- and sub-categories that can be used to describe Human-Automation Interaction in production. The following three key-categories were found: *Human, Automation and Interaction centered*. Although they cannot account for the full view of the interaction between humans and automation, they can simplify the otherwise complex task of understanding interaction breakdowns. In the paper an interaction scenario was presented where the sub-categories *Levels of Automation, Trust and reliability* and *Automation use* were investigated further. It was seen that *usability* i.e. how automation is *used* is an important aspects of interaction and that individual and perceived experience measures should be studied further. This gives an indication of how concepts from all three key-categories can be used to both describe and measure interaction in a production context.

Future research includes deriving hypothesis based on the findings and to test the impact of sub-categories connected to the found key-categories. The research aims towards finding a model that can be used to measure interaction to predict breakdowns and to find an optimal use of the human as a resource.

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7. REFERENCES

[1] Sheridan, T.B. and R. Parasuraman (2005). Human-Automation Interaction, *Reviews of Human Factors and Ergonomics,* **vol. 1**, no. 89, pp. 89-129.

[2] Sheridan, T.B. (1995). Human centred automation: oxymoron or common sense? *Intelligent Systems for the 21st Century, IEEE international*, pp. 6.

[3] Bustamante, E.A., Madhavan, P., Wickens C. D., *et al.* (2009). Current Concepts and Trends in Human-Automation Interaction. *Human Factors and Ergonomics Society Annual Meetings Proceedings.*

[4] Lee, J. D. (2008). Review of a pivotal Human Factors Article: "Human and Automation: Use, Misuse, Disuse, Abuse". *Golden anniversity special issue of Human Factors,* **vol. 50**, no. 3, pp. 404-410.

[5] Parasuraman, R. and V. Riley (1997). Human and Automation: Use, Misuse, Disuse, Abuse. *Human Factors,* **vol. 39(2)**, no. 230-253, 1997.

[6] Merritt, S. M. and D. R. Ilgen (2008). Not All Trust is Created Equal: Dispositional and History-Based Trust in Human Automation Interaction. *HUMAN FACTORS: The Journal of the Human Factors and Ergonomics Society,* **vol. 50**, no. 2, pp. 194-210, April 2008.

[7] Sarter, N. B., Woods, D. D. and C. E. Billings (1997). *Automation Surprises*. Handbook of Human Factors & Ergonomics, second edition, G. Salvendy (Ed.), Wiley

[8] Prewett, M. S., Johnson, R. C. and K. N. Saboe *et al.*, (2010). Managing workload in human–robot interaction: A review of empirical studies. *Journal of Computers in Human Behavior*.

[9] Endsley, M. R. (1996) Automation and Situational Awareness. *Automation and Human Performance: Theory and Application*, L. Erlbaum, ed., pp. 163-181, Mahwah, NJ.

[10] Endsley, M. R. and D. Kaber (1999). Level of automation effects on performance, situation awareness and workload in a dynamic control task. *Ergonomics,* **vol. 42**, no. 3, pp. 462-492, 1999.

[11] Parasuraman, R and V. Riley (1997). Humans and Automation: Use, Misuse, Disuse, Abuse. *HUMAN FACTORS: The Journal of the Human Factors and Ergonomics Society,* **vol. 39**, no. 2, pp. 230-253.

[12] Norman, D. A. (1990). The Problem with Automation: Inappropriate Feedback and Interaction, not Over-Automation. *Philosophical Transactions of the Royal Society of London,* **vol. 327**, no. 1241, Human Factors in Haxardous Situations, pp. 585-593, April 12.

[13] Endsley, M. R. (1997). Level of Automation: Integrating humans and automated systems. *Human Factors and Ergonomics Society Annual.*

[14] Miller, C. A. and R. Parasuman (2003) Beyond Levels of Automation: An Architechture for More Flexible Human-Automation Collaboration. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*. **vol 47 (1)**, pp. 182-186.

[15] Cuevas, H. M., Fiore, S. M. and B. S. Caldwell *et al.* (2007). Augmenting Team Cognition in Human-Automation Teams Performing in Complex Operational Environments. *Aviation, Space and Environmental Medicine,* **vol. 78**, no. 5, Section II, pp. 63-70.

[16] Galster, S. M., Bolia, R. S. and R. Parasuman (2002). The Application of a Qualitative Model of Human-Interaction with Automation: Effects of Unreliable Automation on Performance. *in The Role of Humans in Intelligent and Automated System HFM Symposium*, Warsaw, Poland, 2002.

[17] Sanchez, J. (2009). Conceptual Model of Human-Autiomation Interaction. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*. October 2009, **vol. 53** no. 18 1403-1407.

[18] Corbin, J. M. and A. Strauss (1990). Grounded theory research: Procedures, canons, and evaluative criteria. *QUALITATIVE SOCIOLOGY,* **vol. 13**, no. 1, 1990.

[19] Steinfeld, A., Lewis, M., and T. Fong *et al.* (2006). Common Metrics for Human-Robot Interaction. Proceedings of the 1st ACM SIGCHI/SIGART Conference on Human-Robot Interaction. pp 33-40, Salt Lake City, Utah, USA.

[20] Fasth, Å. (2009). *Measuring and analysing Levels of Automation in assembly systems - For future proactive systems.* Licentiate thesis. Department of Product and Production development, Production Systems, Chalmers University of Technology, Gothenburg, Sweden.

[21] Frohm, J. (2008). Levels of Automation in production systems. Doctorial thesis, Department of production system, Chalmers University of technology, Gothenburg.

[22] Fasth, Å., Stahre, J. and K. Dencker (2008). Analysing changeability and time parameters due to levels of Automation in an assembly system. Flexible Automation and Intelligent Manufacturing, FAIM2008, Skövde, Sweden.

[23] Fereidunian, A., Lucas, C. and H. Lesani *et al.* (2007). Challenges in Implementation of Human-Automation Interaction Models. *in Mediterranian Conference on Control and Automation*, Athens, Greece.

[24] Miller, C. A., and R. Parasuraman (2007) Designing for Flexible Interaction Between Humans and Automation: Delegation Interafaces for Supervisory Control. *HUMAN FACTORS: The Journal of the Human Factors and Ergonomics Society,* **vol. 49**, no. 1, pp. 57-75.

[25] Mattsson, S., Fasth, Å. and C. Berlin *et al.* (2012). Definition and Use of Interaction-Time in Final Assembly. *submitted to the 12th Swedish Production Symposium*, Linköping, Sweden.

[26] Parasuraman, R. and C. D. Wickens (2008. Humans: Still Vital After All These Years of Automation. *Golden anniversity special issue of Human Factors,* **vol. 50**, no. 3, pp. 511-520.

[27] Sanchez, J (2009). Conceptual Model of Human-Automation Interaction. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*. October 2009, **vol. 53** no. 18 1403-1407.

[28] Lee, J. D., and K. A. See (2004). Trust in Automation: Designing for Appropriate

Reliance. *HUMAN FATORS,* **vol. 46**, no. 1, pp. 55-80, Spring 2004.
[29] Johnson, R. C., Saboe, K. N. and L. R. Elliott (2009). Autonomy and Automation Reliability in Human-Robot Interaction: A Qualitative Review. Proceedings of the Human Factors and Ergonomics Society Annual Meeting. October 2009, **vol. 53,** no. 18, pp. 1398-1402.
[30] Parasuraman, R., Sheridan, T. B. and C. D. Wickens (2000). A model for types and levels of human interaction with automation. *IEEE transactions on system, man, and cybernetics - Part A: Systems and humans,* **vol. 30**, no. 3, pp. 286-296.
[31] Moray, N., Inagaki, T. and M. Itoh (2000). Adaptive Automation, Trust, and Self-confidence in Fault Management of Time-Critical Tasks. *Experimental Psychology: Applied,* **vol. 6**, no. 1, pp. 44-58.
[32] Groover, M. P. (2001). *Automation, production systems, and computer-integrated manufacturing*, 3 ed., Upper Saddle River, N.J.: Prentice Hall.
[33] Bellgran, M. and K. Säfsten (2005). *Produktionsutveckling - Utveckling och drift av produktionssystem*, Lund, Sweden: Studentlitteratur.
[34] Kaber, D. B. and M. R. Endsley (2003). The effects of level of automation and adaptive automation on human performance, situation awareness and workload in a dynamic control task. *Theoretical issues in ergonomic science.*
[35] Kaber, D. B., Stoll, N. and K. Thurow *et al.* (). Human–Automation Interaction Strategies and Models for Life Science Applications. *Human Factors and Ergonomics in Manufacturing,* **vol. 19**, no. 6, pp. 21.
[36] Repperger, D. W. and C. A. Phillips (2009). Part 17 The Human Role in Automation. *Automation Theory and Scientific Foundations*. Springer Handbook of Automation. Wiley.
[37] Osman, M. (2010). Controlling Uncertainty: A Review of Human Behavior in Complex Dynamic Environments. *Psychological Bulletin,* **vol. 136**, no. 1, pp. 65-86, Jan 2010.
[38] Parasuraman, R. and D. H. Manzey (2010). Complacency and Bias in Human Use of Automation: An Attnetional Integration. *HUMAN FACTORS: The Journal of the Human Factors and Ergonomics Society,* **vol. 52**, no. 3, pp. 381-410, June 2010.
[39] Inagaki, T. (2003). Adaptive Automation: Sharing and Trading of Control. *Handbook of Cognitive Task Design*, 8, E. Hollnagel, ed., LEA, 2003, pp. 147-169.
[40] Prewett, M. S., Johnson, R. C. and K. N. Saboe *et al.* (2010). Managing Workload in Human-Robot Interaction: A Review of Empirical Studies," *Computers in Human Behavior*, vol 25 (5), September 2010, Pp 840–856.
[41] Bolton, M. L. and E. J. Bass (2010). Formally verifying human–automation interaction as part of a system model: limitations and tradeoffs. *Innovations Syst Softw Eng*, pp. 13, 25 March 2010, 2010.
[42] Bolton, M. L. and E. J. Bass (2011). A Systematic Approach to Model Checking Human–Automation Interaction Using Task Analytic Models. *IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS—PART A: SYSTEMS AND HUMANS*.
[43] Ponsa, P., Vilanova, R. and B. Amante (2011). Human Intervention and Interface Design in Automation Systems. *Interational Journal of Computers, Communications & Control,* **vol. 6**, no. 1 (March), pp. 166-174.

REFERENCES IN LITERATURE STUDY

1.	Parasuraman et al. [30]	2000
2.	Moray et al. [31]	2000
3.	Groover [32]	2001
4.	Galster et al. [16]	2002
5.	Miller et al. [14]	2003
6.	Lee et al. [28]	2004
7.	Bellgran [33]	2005
8.	Steinfeld et al. [19]	2006
9.	Cuevas et al. [15]	2007
10.	Fereidunian [23]	2007
11.	Miller et al. [24]	2007
12.	Kaber et al. [34]	2003
13.	Merritt et al. [6]	2008
14.	Lee et al. [4]	2008
15.	Kaber et al. [35]	2009
16.	Parasuraman et al. [26]	2008
17.	Repperger et al. [36]	2009
18.	Sanchez [27]	2009
19.	Bustamante et al. [3]	2009
20.	Johnson et al. [29]	2009
21.	Osman [37]	2010
22.	Parasuraman et al. [38]	2010
23.	Inagaki [39]	2010
24.	Prewett et al. [40]	2010
25.	Bolton et al. [41]	2010
26.	Bolton et al. [42]	2011
27.	Ponsa et al. [43]	2011

APPENDIX A: TABLES OF LITERATURE STUDY

Table A1: Central concepts divided by key-categories in recent Human-Automation Interaction research

Key-categories	**Central concepts**	**Frequency of Central concepts in Key-category**
Human Centered	Trust/reliability, Workload, Complacency/self-confidence, Safety, Situational Awareness, Social, Reliance, Attention, Authority, Decision-making, Learning, Perception and Management	33
Automation Centered	Levels of Automation, Performance, Changes, Error/failure management, Task, Allocation, Cost/economy, Devices, Navigation, Operational Management and Maintenance	32
Interaction Centered	Usability, Adaptation, Communication, Support and aids, Team performance, Automation bias, Coordination, Compliance, Control sharing and trading, Information, Efficiency and Team Cognition	25

Table A2: Central concepts in recent Human-Automation Interaction research

Central concepts	Key-Categories	Number of concepts in category	Author/-s
Trust/reliability	Human Centered	10	Repperger et al., 2009; Cuevas et al., 2007; Bustamante et al., 2009; Moray et al., 2000; Parasuman et al., 2008; Merritt et al., 2008; Johnson et al., 2009, Lee et al., 2004; Sanchez 2009; Bustamante 2010;
Workload		4	Miller et al., 2007; Prewett et al., 2010; Parasuman et al., 2008
Complacency/self-confidence		3	Bustamante et al., 2009; Parasuman et al., 2010; Moray et al., 2008
Safety		3	Repperger et al., 2009; Lee, 2008; Ponsa et al., 2011
Situational Awareness		3	Miller et al., 2007; Parasuman et al., 2008; Kaber et al., 2003
Reliance		2	Bustamante et al., 2009; Parasuman et al., 2008
Social		2	Steinfeld et al., 2006; Repperger et al., 2009
Attention		1	Fereidunian et al., 2007
Authority		1	Repperger et al., 2009
Decision-making		1	Osman, 2010
Learning		1	Osman, 2010
Perception		1	Steinfeld et al., 2006
Management		1	Steinfeld et al., 2006
Levels of Automation	Automation Centered	9	Fereidunian et al., 2007; Miller et al., 2003; Miller et al., 2007; Bustamente et al., 2009; Ponsa et al., 2011; Parasuman et al., 2000; Parasuman et al., 2008; Sanchez, 2009; Kaber et al., 2009
Performance		4	Miller et al., 2007; Repperger et al., 2009; Lee, 2008; Sanchez, 2009
Changes		4	Steinfeld et al., 2006; Repperger et al., 2009; Osman, 2010; Moray et al., 2008
Error/failure management		3	Bustamente et al., 2009; Bolton, 2011; Moray et al., 2000
Task		3	Steinfeld et al., 2006; Miller et al., 2003; Bolton et al., 2010
Allocation		3	Steinfeld et al., 2006; Miller et al., 2003; Bolton et al., 2010
Cost/economy		2	Repperger et al., 2009; Bustamante et al., 2009
Navigation		1	Steinfeld et al., 2006
Operational environment		1	Bolton et al., 2010
Maintenance		1	Ponsa et al., 2011
Devices		1	Bolton et al., 2010
Automation use	Interaction Centered	6	Miller et al., 2007; Bustamante et al., 2009; Lee, 2008; Merritt et al., 2008; Sanchez, 2009; Johnson et al., 2009;
Adaptation		4	Repperger et al., 2009; Bustamante et al., 2009; Moray et al., 2000; Parasuman et al., 2008
Communication		3	Cuevas et al., 2007; Ponsa et al., 2011; Steinfeld et al., 2006
Support and aids		2	Galster et al., 2002; Bustamante et al., 2009
Team Performance		2	Fereidunian et al., 2007; Cuevas et al., 2007
Information		2	Galster et al., 2002; Parasuman et al., 2000
Efficiency		1	Miller et al., 2007
Team Cognition		1	Cuevas et al., 2007
Control sharing and trading		1	Inagaki, 2010
Automation bias		1	Parasuman et al., 2010
Coordination		1	Cuevas et al., 2007
Compliance		1	Parasuman et al., 2008