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Information Ergonomics and Cognitive Dissonance by AI in HUMINT/OSINT Processes

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ABSTRACT

The study explores the balance between enhancing situational awareness and maintaining good information ergonomics in AI-supported HUMINT/OSINT processes. The proposition for the experimental research was the leveraging effect of organizing and filtering as well as recognition algorithms in HUMINT and OSINT. Increased effectiveness of the due to less cognitive load and better fit to information processing. Especially repetitive activities as well as maintaining attention on several instances of critical events call for robust and explainable methods for information processing. The key issue is maintaining situational awareness on level of intelligence tasks as well as on the meta-level, i.e. organizing intelligence tasks. Simple algorithms and AI powered methods can enhance situational awareness in time-critical operations, but they may also cause cognitive dissonance as operators question the accuracy of the AI-provided information, leading to additional cognitive load and poor information ergonomic state. The results are based on constructive research process. Methods were designed by operators yet put into action by external developers. Experimental phase consisted of reanalysis of intelligence data and information. Validation in this setting is based of expert assessment, evidence on good functionality, and effect on information ergonomics. Acceptance and trust in AI are crucial to avoid cognitive dissonance and increased cognitive load and those factors are also discussed in the paper.

Keywords: OSINT, HUMINT, Situational awareness, Information ergonomics, Cognitive dissonance

EFFICIENT INFORMATION PROCESSING OR CONTROL OVER THE PROCESS

Complexity and time criticality describe the environment in which military personnel operate. Boyd's OODA loop is one of the most commonly used models aimed at describing military decision-making (Stanton et al., 2008, 16). The OODA loop is a cyclical, internally linked model of military decision-making, consisting of observe, orient, decide, and act. The model has been used to describe the importance of decision-making efficiency. Decision-making requires situational awareness, so it is essential to support the achievement and maintenance of good situational awareness as efficiently as possible, especially in the most time-critical tasks. In the context of intelligence, the amount of data and information refined challenges human capabilities and thus low-tech and high-tech solutions for automated, or even autonomous, information processing methods are constantly developed. Current progress with algorithms and for example with generative AI has highlighted AI as a silver bullet to solve all possible information management problems. There are several examples of utilising natural language processing, machine learning, machine vision, neural networks and such, yet still the optimal teaming and augmenting humans with technology seem to be most important areas of development.

The starting point for the design of management systems is situational awareness. Situational awareness can be examined at the level of an individual, a team or a system (Stanton, 2017). To put it simply, situational awareness means understanding what is happening around you (Stanton, 2017). Endsley (1997; 2017) divides situational awareness into three levels: perception, understanding, and projection of the future. Situational awareness is a prerequisite for decision-making that leads to action that further shapes the state of the world and thus produces feedback for perception. Factors related to the task, the environment and the individual affect the formation of situational awareness. In practice, this means that it depends on how complex the system is, how it presents information and what kind of interaction there is with it (cf. Stanton et al., 2009).

The information needed to support decision-making must be provided as an information product in a form that is as easy to absorb as possible, so that the process to be controlled does not suffer from an additional information processing cycle (cf. Choo, 2002). At the core of information driven operation support is a focus on essential information. When time pressure is added to the equation, you get a complex optimization problem. The factors to be optimized are the completeness of the information, the amount of information presented, and the degree of information processing. In traditional information management process models, such as Choo (2002) or Savolainen (2010), the above-mentioned factors are not specifically addressed, but optimization is thought to take place implicitly. However, it has been pointed out in the literature that time pressure in particular places demand on information and its use. As Franssila et al. (2015) point out, this is a significant phenomenon related to ergonomics. Improving information ergonomics has a performance-promoting effect and reduces stress in the work situation (Okkonen et al., 2018).

Taking the definition of information ergonomics discussed in Franssila et al. (2015) and Okkonen et al. (2017) the load of information processing, the amount of information, and time pressure affect the ergonomic state of an operator. The foundation of sound judgement and making decisions is right, sufficient and targeted information about the key factors. A human-technology interaction perspective views AI as an activity, which assists human to filter, manage, analyse and refine information in order to gain and maintain SA. Crowder, Friess and Carbone (2013) underline the independent role of technology in assisting the operators. In order to better utilise the human information processing capacity, the AI refined information should be presented in a form which minimises the cognitive load (cf. Endsley and Rodgers, 1994). This can be achieved as AI excels with speed and ability to process large amount of information (Shrestha et al., 2019). AI can support gaining and maintaining all three levels of SA and decision-making. However, these support functions require that characteristics, rules and dependencies of the system elements have been identified, and the AI has been taught and/or programmed accordingly.

For the information ergonomics, the impact is still evident as AI curates the content, i.e. by the predesignated rules it for example highlights the most noteworthy objects and keeps the attention on the relevant factors as discussed in Crowder et al. (2012). On the other hand, the mode of the presentation has also affected as some information is presented different and it no longer require operator processing. Enhanced information ergonomics in the context of this paper is the product, not sum, of automated information processing combined with more accurate, condensed and quicker presentation of what is what is perceived and what is [possibly] happening. Related to organisational intelligence cycle the augmenting role of artificial intelligence are sensing, perception, interpretation, and memory (Choo, 2002; Jarrahi, 2018). Adaptive behaviour is dependent on human attributes such as creativity ja creativity and the trust in on the sound judgement of the operators, not the algorithm. The utilisation of the algorithmic technology has evidently dual effect on ergonomic state by load of information processing and sense making. If the information processing is done by transparent and explainable methods, there is no room for cognitive dissonance cause by conflict between expectations and delivered information. Moreover, in such situation cognitive dissonance leads to poor ergonomics as conflict leads to reanalysis and double-checking. Acceptance and trust in AI are crucial to avoid cognitive dissonance and increased cognitive load by additional reprocessing.

The balance between enhancing situational awareness and maintaining good information ergonomics in AI-supported HUMINT/OSINT processes is balancing between ease of processing and human control over the process. The proposition for the experimental research was the leveraging effect of organizing and filtering as well as recognition algorithms in HUMINT and OSINT. Increased effectiveness of the due to less cognitive load and better fit to information processing. Especially repetitive activities as well as maintaining attention on several instances of critical events call for robust and explainable methods for information processing. The key issue is maintaining situational awareness on level of intelligence tasks as well as on the meta-level, i.e. organizing intelligence tasks. Simple algorithms and AI powered methods can enhance situational awareness in time-critical operations, but they may also cause cognitive dissonance as operators question the accuracy of the AI-provided information, leading to additional cognitive load and poor information ergonomic state. The results are based on constructive research process aiming to develop augmenting tools for manual information management process. Methods were designed by operators yet put into action by external developers. Experimental phase consisted of reanalysis of intelligence data and information. Validation in this setting is based of expert assessment of evidence on good functionality, and effect on information ergonomics and those factors are also discussed in the paper.

The two key topics related to human factors related with situational awareness are ergonomics and cognitive dissonance as discussed in Okkonen et al. (2021). Utilisation of technology underlines the augmenting role of the AI human technology and interaction perspective should take into account when implementing it as stated by Duan et al. (2019). The acceptance and trust are related to several factors such as motivation, user perception of the presence, and expectations on performance and utility. Expectations on human like behaviour and delivering process virtues as well as securing operations relate also to acceptance (Mahadevaih et al., 2020). This is also important factor when assessing the task performance as productive utilisation of technology requires acceptance and opposite situation can be inflicted by several ways. If there is lack of trust, there will be high risk for cognitive dissonance and double checking leads to vicious circle of increasing cognitive load and poor information ergonomics. The issues of trust and acceptance should be recognized as first order condition for utilisation is delivering utility with key features or functionalities. This technological intention itself is not sufficient solely as also user's role in operating environment has great significance. Also, the subjective sense of workload while processing information has significance. Cognitive dissonance, i.e. possible conflict between precepted, experienced and projected is has effect via human operators. The source for cognitive dissonance, i.e. is it caused by technology or mental factors, should be addressed by the perspectives of technology relationship, sense of self-efficacy, motivation as user, and user personality,

METHOD DEVELOPMENT AND KEY FINDINGS

The method developed is aimed to support and leverage information classification, combination and visualisation by the analyst at operative level. To keep it simple, the utilised data is an extract of data already classified and analysed by the informants. There were three workshops to set the objectives for development, seeking possible use cases, and prioritising most feasible cases. The need for AI-powered method relies on need for lesser cognitive load, easier perception of deviating instances, better situational awareness by visualisation or attention methods, and automated clustering by the location and type of event. The most important pieces of data are about temporal and spatial attributes of incidents. Along the process steps the validation of domain and methods was conducted by expert validation.

Putting any event in exactly the right place at the right time based on non-structured information provided by laymen is not the most straightforward tasks. There is trade-off between human fuzziness, i.e ability to recognize minor hints and clues, and limited processing capability compared to algorithmic accuracy and [almost] unlimited computing capability. Since intelligence is extremely dull and seldom something meaningful surfaces, it is better to rely on technology. Human capacity is reserved for interpreting, sense making, and decisions.

The dataset for entity extraction consists of short Finnish-language digital texts, which are a few sentences long. Recognition of spatial and temporal entities is performed using a FinBERT-based model. The model extracts structured entities such as persons, organizations, locations, geopolitical entities, products, events, and dates. Because it is fine-tuned for Finnish text, FinBERT has demonstrated higher accuracy in Finnish-language NLP tasks compared to multilingual models, particularly in NER, part-of-speech tagging, and dependency parsing (Virtanen et al., 2019). Topic modelling is used to classify short Finnish-language texts into thematic clusters (BERTopic). The sentence-BERT model used in this study was trained on a large corpus of Finnish texts (Luoma et al., 2020).

The extracted locations are enriched with geographic locations and administrative regions from an official database. Since Finnish place names exhibit variability in spelling and formatting, a matching algorithm is applied. This allows for interactive filtering and for the recognized entities to be displayed as point features on an interactive map, as well as enables a spatial distribution analysis. One suitable approach is kernel density estimation, which smooths spatial data into a continuous intensity surface and can be applied to identify areas with a high frequency of entity mentions.

The pipeline for employment of natural language processing techniques is executed locally. Named entity recognition and topic modelling are performed using locally stored models, while geospatial processing is conducted on precomputed spatial datasets.

The pipeline described does still encounter significant challenges. Finnish has far fewer annotated corpora than major world languages. While FinBERT and TurkuNLP have improved NLP performance, models still struggle with domain adaptation. Furthermore, Finnish presents particular for NLP due to its morphological complexity, flexible word order, compound words, ambiguity in named entities and temporal expressions, and dialectal variation.

The numerous grammatical cases in Finish language result in a single root word having numerous inflected forms. This affects entity recognition, as models must account for variations beyond simple string matching. To further complicate the matter, long compound words are common, which traditional tokenization struggles to segment correctly. NLP models often misidentify components of compounds as separate words, affecting topic modelling and named entity recognition. Furthermore, Finnish has a free word order, meaning that sentence structure does not always determine grammatical function. Instead, meaning is conveyed through case endings. Positional heuristics, which which can be employed with syntactically rigid languages like English, cannot be utilized with Finish texts.

Adding to these complexities, Finnish dialectal variation presents another obstacle for NLP. While standard Finnish serves as the primary basis for most NLP models, numerous regional dialects diverge significantly in vocabulary, morphology, and phonetics. Substantial differences also exist between spoken and written Finnish, with colloquial forms differing greatly from formal texts, requiring NLP models to be trained on multiple registers to improve generalization. Therefore, named entity recognition and topic models are likely to have diminished performance when employed to unofficial texts from across the country.

Additionally, a heuristic method for extracting spatial entities from the text corpus by computing jaro-winkler distances of words in the corpus to officially recognized place names in Finland was implemented. In the corpus, place names are often included as “hashtags” in lieu of some related text. The hashtags are extracted, and each hashtag is matched to all known places in a specific region of Finland. Jaro-winkler distance is used due to its characteristic weighting of a matching string prefix, which is expected to be more accurate than unweighted string matching, due to the characteristic of the Finnish language corpus, where many inflections are affixes.

Whenever the heuristic finds an exact word match between a tag and an official place name, it is considered the correct result, and the heuristic stops. If an exact match with an official place name is not found from the tags, the algorithm proceeds to further split the tags into component words, to account for cases where the place name is compounded from e.g. the name of a city, and the name of a place in the city. If an exact match is not found this way, we further match words in the entire text content to place names in the specified region.

Similarly to the FinBERT based model, the heuristic fails to find the correct spatial entities reliably unless the place names are in uninflected form. Place names are often close to common words, or even based on common words, which causes the results of the search to be polluted with many close matches. If the correct spatial entity exists in inflected form in the corpus, it is often one of many close semantic matches, but the algorithm cannot differentiate them meaningfully. Furthermore, most Finnish regions contain duplicate names that are identified by some other characteristic, such as subregion, municipality, or city, which the algorithm cannot distinguish from each other. It can be concluded that the heuristic is very dependent on the quality and structure of the input text. The further the search space can be narrowed before applying the algorithm (municipalities, regions, subregions), the more accurate the results will be.

Like described above even simple classification and clustering by two attributes from non-structured data is somewhat challenging there are also requirements for the data. Better structured data, i.e. separating time of submission and event or separating location of event and location where the information is submitted would help in clustering. Further, automated analysis on the content could also benefit of such framing.

CONCLUDING REMARKS

As stated above, the dynamic information environment calls for robust applications of algorithmic technology. There seems to be misconceptions on the logic, capabilities or operating logic of artificial intelligence. Current hype with generative AI leads to false expectations on the potential of technology. Of course it is easier to team up with human like agent, yet user interface or use modality are not essential. In the domain of intelligence operation and data security, method transparency and explainability are the most important requirements.

The algorithmic capabilities of operators or analyst serve as moderating factors as those people have capacity to both interpret the contents on intelligence data and information, but they also have understanding on the information process augmenting technology. Such knowledge should overcome the effects of cognitive dissonance. On the other hand, if the algorithm is non-explicable or the system is a black box, experienced operators might have reasonable doubt and that has effect on ergonomics by increased cognitive load.

Next phase in studying the algorithmic processing capacity augmentation will concentrate on [quasi]experiment on information processing performance in order to provide normative results on human/technology -ratio or on how human-autonomy teaming should be conducted. Additionally, the information and knowledge dynamics should be studied from the perspective of different roles in the process. There are evident tasks humans are better at, yet also those machines are better at. Teaming and cohesion in such somewhat complex construct are based on perceives usefulness of technology and perceived ease of use of technology. In many cases there are issues with different users especially with user experience, thus it might have effect on acceptance of the technology.

Finally, the role of humans can be reduced to continuum man-in-the-loop, man-on-the loop, or man-out-the-loop. Due to almost infinite time horizon and continuous processing on intelligence data technology plays key role in collecting, classification, and organising data and information. Even basic analysis such as clustering by set rules is on the domain of machine. Drawing conclusions, refining knowledge, making decisions, and taking action are domains of human. As the technology advances the distinction might be less dramatic.

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REFERENCES

Choo, C. (2002). Information Management for the Intelligent Organization: The Art of Scanning the Environment (3rd ed.). Medford, NJ: Information Today, Inc.

Crowder, J., Friess, S., & Carbone, J. (2013). Artificial cognition architectures. New York: Springer. ISBN 978-1-4614-8071-6.

Crowder, J., Scally, L., & Bonato, M. (2012). Applications for intelligent information agents (I2As): Learning agents for autonomous space asset management (LAASAM). In Proceedings of the International Conference on Artificial Intelligence, ICAI'12, Las Vegas, NV.

Duan, Y.; Edwards, J. S.; & Dwivedi, Y.K. (2019). Artificial intelligence for decision making in the era of Big Data - evolution, challenges and research agenda. International Journal of Information Management, 63–71.

Endsley, Mica (1995). Toward a Theory of Situation Awareness in Dynamic Systems. https://www.researchgate.net/publication/210198492_Endsley_MR_Toward_a_Theory_of_Situation_Awareness_in_Dynamic_Systems_Human_Factors_Journal_371_32-64.

Endsley, Mica (2017). From Here to Autonomy: Lessons Learned from Human–Automation Research. Saatavilla: https://journals.sagepub.com/doi/10.1177/0018720816681350

Endsley, M and Rodgers, M. (1994) Situation awareness information requirements analysis for en route air traffic control, in Proceedings of Human Factors Ergonomics Sociesty Annual Meeting, vol. 38, no. 1, pp. 71–75. doi: 10.1177/154193129403800113.

Franssila, H., Okkonen, J., Savolainen, R. (2015): Developing measures for information ergonomics in knowledge work, Ergonomics, Vol. 58. doi: 10.1080/00140139.2015.1073795.

Jarrahi, M. H. (2018). Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision Making. Business Horizons, 577–586.

Luoma, J., Pyysalo, S., & Oikarinen, E. (2020). A broad-coverage corpus for Finnish named entity recognition. Proceedings of the 12th International Conference on Language Resources and Evaluation (LREC 2020), 4615–4624.

Mahadevaiah, G.;Bermejo, I., P., Jaffray, D., Dekker, A, & Wee, L. (2020). Artificial intelligence-based clinical decision support in modern medical physics: Selection, acceptance, commissioning, and quality assurance. Medical Physics, 228–235.

Okkonen, J., Heimonen, T., Savolainen, R., & Turunen, M. (2017). Assessing Information Ergonomics in Work by Logging and Heart Rate Variability. in T. Ahram and C. Falcão (eds.), Advances in Usability and User Experience, Advances in Intelligent Systems and Computing 607, Springer. doi: 10.1007/978-3-319-60492-3_41.

Okkonen, J., Hakulinen, J., Jalava, M., Keskinen, T., Mansikka, H., Turunen, M. (2021) Design for AI-enhanced operator information ergonomics in time-critical environment in Advances in Neuroergonomics and Cognitive Engineering, Proceedings of the AHFE 2021 Virtual Conferences on Neuroergonomics and Cognitive Engineering, Industrial Cognitive Ergonomics and Engineering Psychology, and Cognitive Computing and Internet of Things in Lecture Notes in Networks and Systems (LNNS, volume 259). doi: htpp://doi.org/10.1007/978-3-030-80285-1_2

Shrestha, Y., Ben-Menahem, S. and von Krogh, G. (2019) Organizational Decision-Making Structures in the Age of Artificial Intelligence, California Management Review, 61(4), pp. 66–83. doi: 10.1177/0008125619862257.

Savolainen, R. (2010) Tiedonhankintatutkimuksen lähtokohtia pp. 75–115 In Serola, S. (ed.) Ote informaatiosta: Johdatus informaatiotutkimukseen ja interaktiiviseen mediaan. Avain.

Stanton, Neville & Baber, Chris & Harris, Donald. (2008). Modelling Command and Control.

Stanton, Neville & Jenkins, Daniel & Salmon, Paul & Walker, Guy & Revell, Kirsten & Rafferty, Laura. (2009). Digitising Command and Control: A Human Factors and Ergonomics Analysis of Mission Planning and Battlespace Management. https://doi.org/10.1201/9781315577241

Stanton, N. A., Salmon, P. M., Walker, G. H., Salas, E., & Hancock, P. A. (2017). State-of-science: situation awareness in individuals, teams and systems. Ergonomics, 60(4), 449–466. https://doi.org/10.1080/00140139.2017.1278796

Virtanen, A., Kanerva, J., Ilo, T., Luoma, J., Laippala, V., Salakoski, T., Ginter, F., & Pyysalo, S. (2019). Multilingual BERT and representation learning for Finnish. arXiv preprint arXiv:1912.07076.