Cognitive decision-making strategies in patient flow management

Matthew Woodward[1], Julie Gore[2], Fotios Petropoulus[3] & Christos Vasilakis[3]

[1]The Healthcare Improvement Studies (THIS) Institute, University of Cambridge, [2] Department of Organisational Psychology, Birkbeck, University of London, [3] School of Management, University of Bath

SUMMARY

Decision-making for hospital patient flow management is a time-constrained task for a dynamic problem, but little is known about the cognitive strategies required for this type of task. The Skills-Rules-Knowledge model of cognition was used to study the decision-making strategies of clinical coordinators and patient flow managers in acute medical units in two hospitals. For time-constrained decisions in an environment with a plethora of dynamic data, a rule-based feedforward strategy was predominant. Additionally, decision makers applied their tacit knowledge of bed demand profiles to project the future situation and to compensate for delays that were inherent in the patient transfer process.

KEYWORDS

Patient flow, decision-making, Skills-Rules-Knowledge model, operations management

Introduction

Patient flow management is characteristic of a dynamic decision-making task – it requires interrelated and time-constrained decisions to maintain control of a system that changes due to both the decision-maker's actions and exogenous events. The majority of research on dynamic decision-making uses a methodology of laboratory-based simulations with students as participants. These present control tasks with a single goal such as temperature control, water processing plant operation or post sorting (Gonzalez, 2003; Gonzalez et al., 2017; Lerch & Harter, 2001; Rosa et al., 2020) and have limited generalisability to decisions in applied work settings. This study took a naturalistic decision-making (NDM) approach (Gore et al., 2015) and applied field-based methods to research the cognitive strategies used by clinical coordinators and operations managers to make decisions about patient flow in hospitals.

Initial participant observations found that a high volume of data was available in the information environment and thus it was anticipated that there may be a tension between intuitive and analytical decision processes. Thus, Rasmussen's skills-rules-knowledge model (Rasmussen, 1983)was selected as a theoretical frame because it can represent both modes of decision-making and it was developed in the context of system control.

Methodology

A case study methodology was used with an emphasis on the qualitative methods of participant observations, interviews and chart drawing to elicit cognitive strategies. Quantitative forecasting methods were embedded to evaluate the accuracy of predictions and to enhance explanation and utility. Data was collected from two NHS hospitals with over 100 hours of participant observations and 19 Critical Decision Method (CDM) based interviews (Crandall et al., 2006). Interviews were transcribed and field notes summarised. Analysis was conducted by coding quotations against the skills-rules-knowledge model and the decision ladder (Rasmussen, 1983; Rasmussen & Goodstein, 1987) using the ATLAS.ti software. Participant-drawn charts were assessed for whether they captured key features of the bed demand profile.

Results

Patient flow management is a dynamic problem in which information about the system changes at the level of the patient, the medical unit and the division. It was found that lags in the patient transfer process presented a challenge for the sensemaking stage of decision-making for managers. This resulted in an offset between the situation on the floor and the representation on the bed management systems. The predominant cognitive strategy was rule-based, meaning well-practiced sets of mentally stored rules were applied to make efficient patient-to-space allocations under time pressure. This was complemented by a feedforward strategy to make decisions about future actions, for example patient transfers or pre-emptive adjustments to capacity. It was found that decision-makers held accurate internal representations of intraday admission patterns to support this strategy.

Discussion

Naturalistic decision-making (NDM) theory, such as the Recognition-Primed Decision (RPD) model (Klein et al., 2010) predict that in time-pressured situations an intuitive mode of decision-making will be used. In contrast, this research provides evidence that for a service operations management task, conscious rule-based processes were predominant. Decision-makers were skilled at projecting ahead in time to support a feedforward control strategy and to compensate for delays inherent in the patient flow process. In alignment with the NDM literature, situated experience had fostered the experts' tacit knowledge of bed demand profiles. A challenge for this research was recruitment because patient flow managers and coordinators have demanding roles over long shifts. For analysis, a strength of using the decision ladder was that it brought rigour to the process of coding transcripts and establishing the invoked level of cognition. A limitation was that the elicitation process of participant verbalisation may have made cognitive processes appear more deliberate than they actually were and allowed post-event rationalisations to occur (Ormerod & Ball, 2017).

This research adds to the human factors and ergonomics literature on decision-making by identifying the requisite cognitive skills for managing a dynamic field-based operations problem. It expands on the NDM concept of near-term anticipation (Lipshitz et al., 2001) to include closed loop control for longer time frames. This knowledge can inform the role of individuals' expertise in enabling hospital-level adaptive capacity (Anderson et al., 2020; Back et al., 2017; Wears & Woods, 2007).

References

Anderson, J. E., Ross, A. J., Macrae, C., & Wiig, S. (2020). Defining adaptive capacity in healthcare: A new framework for researching resilient performance. *Appl Ergon*, *87*, 103111. https://doi.org/10.1016/j.apergo.2020.103111

Back, J., Ross, A. J., Duncan, M. D., Jaye, P., Henderson, K., & Anderson, J. E. (2017). Emergency Department Escalation in Theory and Practice: A Mixed-Methods Study Using a Model of Organizational Resilience. *Ann Emerg Med*, *70*(5), 659-671. https://doi.org/10.1016/j.annemergmed.2017.04.032

Crandall, B., Klein, G., & Hoffman, R. (2006). *Working Minds: a Practitioner's Guide to Cognitive Task Analysis*.

Gonzalez, C. (2003). Instance-based learning in dynamic decision making. *Cognitive Science*, *27*(4), 591-635. https://doi.org/10.1016/s0364-0213(03)00031-4

Gonzalez, C., Fakhari, P., & Busemeyer, J. (2017). Dynamic Decision Making: Learning Processes and New Research Directions. *Hum Factors*, *59*(5), 713-721. https://doi.org/10.1177/0018720817710347

Gore, J., Flin, R., Stanton, N., & Wong, B. L. W. (2015). Applications for naturalistic decision-making. *Journal of Occupational and Organizational Psychology*, *88*(2), 223-230. https://doi.org/10.1111/joop.12121

Klein, G., Calderwood, R., & Clinton-Cirocco, A. (2010). Rapid Decision Making on the Fire Ground: The Original Study Plus a Postscript. *Journal of Cognitive Engineering and Decision Making*, *4*(3), 186-209. https://doi.org/10.1518/155534310x12844000801203

Lerch, F. J., & Harter, D. E. (2001). Cognitive Support for Real-Time Dynamic Decision Making. *Information Systems Research*, *12*(1), 63-82. https://doi.org/10.1287/isre.12.1.63.9717

Lipshitz, R., Klein, G., Orasanu, J., & Salas, E. (2001). Taking stock of naturalistic decision making. *Journal of Behavioral Decision Making*, *14*(5), 331-352. https://doi.org/10.1002/bdm.381

Ormerod, T. C., & Ball, L. J. (2017). Cognitive psychology. In *The SAGE Handbook of Qualitative Research in Psychology* (pp. 572-589). SAGE Publications Ltd. https://doi.org/10.4135/9781526405555

Rasmussen, J. (1983). Skills, Rules, and Knowledge; Signals, Signs, and Symbols, and Other Distinctions in Human Performance Models. *IEEE Transactions on Systems, Man and Cybernetics*, *SMC-13*(3), 257-266. https://doi.org/10.1109/TSMC.1983.6313160

Rasmussen, J., & Goodstein, L. P. (1987). Decision support in supervisory control of high-risk industrial systems. *Automatica*, *23*(5), 663-671. https://doi.org/10.1016/0005-1098(87)90064-1

Rosa, E., Dahlstrom, N., Knez, I., Ljung, R., Cameron, M., & Willander, J. (2020). Dynamic decision-making of airline pilots in low-fidelity simulation. *Theoretical Issues in Ergonomics Science*, *22*(1), 83-102. https://doi.org/10.1080/1463922x.2020.1758830

Wears, R. L., & Woods, D. D. (2007). Always Adapting. *Annals of Emergency Medicine*, *50*(5), 517-519. https://doi.org/https://doi.org/10.1016/j.annemergmed.2007.09.018