COMPUTATIONAL STUDY ON DESIGN SPACE EXPANSION DURING TEAMWORK

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ABSTRACT

When observing a design space expansion during teamwork, several studies found that cumulative solution-related issues' occurrence follows a linear trend. Such findings contradict the hypothesis of solution-related issues being characteristic for the later design stages. This work relies on agent-based simulations to explore the emerging patterns in design solution space expansion during teamwork. The results demonstrate trends that accord with the empirical findings, suggesting that a cognitive effort in solution space expansion remains constant throughout a design session. The collected data on agents' cognitive processes and solution space properties enabled additional insights, which led to the detection of four distinct regimes of design solution space expansion.

Keywords: Design cognition, Teamwork, Simulation, Design space expansion

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Cite this article: Perisic, M. M., Štorga, M., Gero, J. S. (2021) 'Computational Study on Design Space Expansion during Teamwork', in *Proceedings of the International Conference on Engineering Design (ICED21),* Gothenburg, Sweden, 16-20 August 2021. DOI:10.1017/pds.2021.69

1 DESIGN SPACE EXPANSION

A design space can be defined as a changing space of potentialities created by a designer while designing (Kan and Gero, 2018). The change in a design space stems from designers' cognitive actions denoted as framing and reframing that iteratively shape both a problem and solution space (Dorst, 2015). During design the problem and the solution spaces are considered to co-evolve (Maher et al., 1996). A co-evolution model of design has been verified in empirical studies (Dorst and Cross, 2001; Yu et al., 2015) and simulated using computational models (Maher, 2000; Maher and Tang, 2003).

As new design issues are created and introduced, the design space changes through expansion. Design space expansion has been linked to creativity (Dorst and Cross, 2001): researchers argued that a larger design space creates more opportunities for generating novel, useful and surprising, i.e., creative designs (Alsager Alzayed et al., 2019; Gero and Kan, 2016). Studies (e.g., Shah et al., 2000) have demonstrated that design space expansion leads to greater design variety and solutions of a higher quality and effectiveness. Therefore, it is not surprising that numerous works aimed at studying (Alsager Alzayed et al., 2019) and supporting design space expansion through the use of, for example, heuristics (Daly et al., 2012) or computational tools (Gero and Kumar, 1993; Han et al., 2018).

Relatedly, several studies explored the rate at which the design space expands in a team setting (e.g., Gero and Kan, 2016; Martinec et al., 2020). For this purpose, studies utilised a cumulative graph of issues' occurrences. Kan and Gero (2017) argued that the cumulative occurrence of design issues demonstrates a cumulative cognitive effort across the design session. By noting each issue's first occurrence (externalised in speech, gesture or sketch), cumulative graphs depict the change in the production of issues over the design session. Building on the theories outlined in (Asimov, 1962; Kannengiesser and Gero, 2012; Pahl and Beitz, 2007), studies have hypothesised that the trend of cumulative new issues' occurrence should follow a logarithmic function with the majority of design issues introduced at the session beginning, followed by a decrease in new occurrences as the session reaches later stages (Gero and Kan, 2016; Martinec et al., 2020).

Contrary to these expectations, these studies consistently found a linear trend in the occurrence of solution-related issues. While the rate at which new problem-related issues are introduced declines towards the session end, new solution-related issues appear at a constant rate throughout the design session. Empirical studies further examined if the different patterns in solution-related occurrence would emerge when a design task, domain or participants' expertise and education level are varied (Gero, Kannengiesser and Pourmohamadi, 2014; Gero, Kannengiesser and Williams, 2014; Kannengiesser et al., 2015). Surprisingly, the linear trend in solution space expansion was found across all cases studied.

This work aims at furthering the study of design solution space expansion in teams by simulating a large number of design sessions and observing the trends in solution generation. A computational model of a design team was developed building on a theory of human cognition (Kahneman, 2011; Miyake and Shah, 1999) and design (Gero, 1990; Gero and Kannengiesser, 2004), and its capability to replicate several empirical results was demonstrated in the previous work (Perišić et al., 2019a; 2019b). In this study, the trends in solution generation emerging from the simulations are contrasted to the empirical results. The following research question is explored:

When working in teams, what are the patterns in the temporal change of the size of design solution space?

In contrast to the existing computational approaches simulating design space expansion (Gero and Kazakov, 1998; Maher and Tang, 2003) that rely on genetic algorithms, the model used in this study represents the details of the designer's cognitive behaviour in an agent. The agent-based model developed bases the individual designer's (i.e., agent's) behaviour on existing design literature and cognitive studies, and the team-level behaviour emerges as a consequence of the interactions among the agents. Thus, utilising the model to study the research question provides the means to gain deeper insights into the cognitive processes potentially underlying the trends observed in empirical studies. In addition to studying whether the individual processes implemented could give rise to the observed team-level trends, utilising the computational simulations enables collecting a large number of design sessions whose analysis could uncover potential, but less prominent, patterns in design space exploration.

2 COMPUTATIONAL MODEL OF A DESIGN TEAM

The agent-based model used in this simulation study comprises cognitive, situated agents working in teams. Each agent's knowledge is represented as a network of design issues, and the agent's cognitive processes are modelled as an activation spreading over the network. Building on the Function-Behaviour-Structure (FBS) ontology (Gero, 1990), each network node represents either a function, behaviour or a structure, and the activation spreading from one node to another corresponds to a particular FBS process. For example, activation spreading over a link connecting a function and a behaviour node represents Formulation. Similarly, when the activation is spread from behaviour nodes to structure nodes, the process is interpreted as Synthesis. Following Gero and Kannengiesser (2004) there are no links between nodes of the same type, nor direct links from function to structure nodes.

The design agents should be capable of generating new structures (i.e., structure nodes) and assessing the structure behaviour to enable Evaluation, Analysis and Reformulation I processes. Since design structures are commonly regarded as networks of parts, each structure node within the agent's mental model is associated with a binary, undirected network, Figure 1. Each behaviour node is associated with a particular network property. These modelling decisions create a natural association between behaviour and structure nodes, thus equipping the agents with the mechanism to determine if a specific behaviour-structure link should exist. For example, one behaviour node may correspond to "having network density below 0.1". By calculating the associated networks' properties, the agents can determine which structure nodes should be connected to this behaviour node. Here, the network's properties calculation corresponds to Analysis, while the process of comparing the sets of obtained and expected behaviour nodes represents Evaluation. If during evaluation, the agent detects a mismatch with the expectations, an activation impulse is sent to function and behaviour nodes relevant to the unmet expectations (Reformulations II and III in the FBS ontology).

Finally, two mechanisms for new structures generation are implemented to enable solution space expansion and simulation of the Reformulation I process. The first structure generation mechanism is based on the act of combining two structures into one. This *union* occurs when two structure nodes are simultaneously sufficiently active in the agent's mental model and consists of overlaying one structure's network over the other. The second structure generation mechanism - *concatenation* - collapses two nodes within the structure's network into one. This mechanism was based on the act of coupling two structure parts (e.g., a keyboard and a screen) into one (a touchscreen). Utilising the two structure-generating mechanisms, the agents can continuously expand the solution space, and the newly generated structures have the potential to display behaviours different from that of the originating structures.

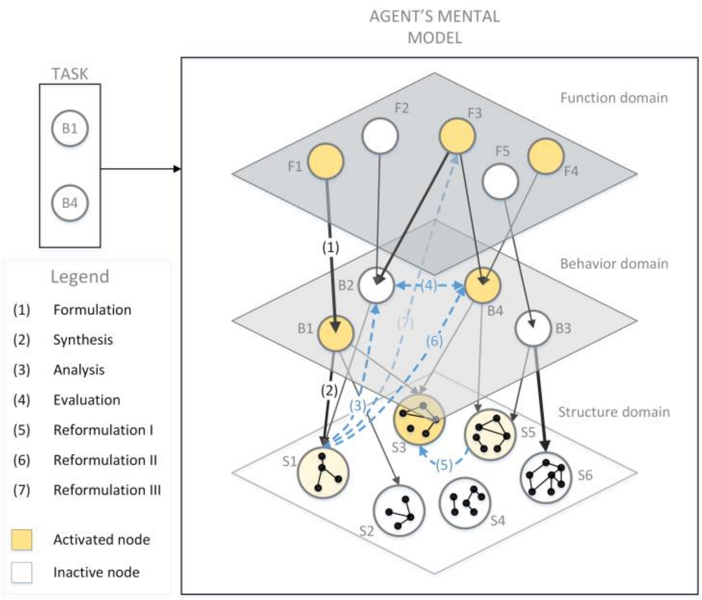

Figure 1. Agent's mental model

A design task is represented as a set of behaviour nodes that a structure has to accommodate to be regarded as a solution. In other words, the task poses requirements on the structure network's properties. At the commencement of a simulation, a task is generated and presented to the agents. The

https://doi.org/10.1017/pds.2021.69 Published online by Cambridge University Press

agents have a memory containing the past tasks' details which enables them to make inferences on which function nodes are relevant for the task at hand. The relevant function nodes activate, and the activation is passed over the knowledge network. However, the knowledge network links differ in their activation transfer capacity. The weight of a link represents ease of its processing, and the amount of activation which can be passed over the link in a single simulation step is proportional to this weight. As the link is used, its weight increases, thus simulating that the knowledge the link represents got more grounded and consequently becomes easier to process.

The notion of link weight is used to represent an agent's expertise area. Each agent is created as having a grounded domain of expertise, which is tied to a combination of behaviour nodes. The relevant links connecting the behaviour nodes within its expertise to the function nodes, as well as to structure nodes, are well-grounded in the agent's mental model. In other words, each agent is familiar with several structures displaying the behaviours specified by its expertise area and is capable of quickly recalling such structures.

A team of agents is created at the simulation's start by randomly selecting agents with diverse knowledge and expertise. The team then starts processing the design task and communicating the relevant design issues. In each simulation step, the agents can share a knowledge element (a link or a structure) that is sufficiently grounded and active in their mental model. If several agents wish to share something with others in a particular step, the agent is chosen randomly. The agents can share a knowledge link connecting two sufficiently active nodes if the link's weight exceeds a predefined threshold. In response, listening agents add or further ground the communicated links in their respective mental models. Similarly, if the agent determines that a sufficiently active structure meets several requirements (i.e., the relevant links get sufficiently grounded), the agent can propose the structure as a solution. The design issues communicated receive an activation impulse in the agents' mental models to simulate the effect of attention dedicated to the communicated messages. If the issue becomes sufficiently active upon registering the message, the agent's focus changes to include this issue. In other words, communication can alter the agent's chain of "thoughts".

For the simulation to terminate, the whole team has to agree upon a single solution. Each time a structure is proposed as a solution, every agent evaluates it against their mental model and presents its evaluation to the team. The simulation finishes when the team reaches a consensus on the suitability of a particular structure.

More details on the model's implementation and performance can be found in previous work (Perišić, 2020). In the context of the study described here, it should be noted, that the model poses no restrictions on the content or timing of the messages exchanged among the agents. In other words, the agents' exploration of problem and solution space, as well as the generation of new structures, are guided solely by each design agent's cognitive processes.

Simulation settings: The simulated teams consisted of three agents, and the limit on the number of simulation steps was set at 1,000. The simulations where the agents found and agreed upon a suitable solution were considered, creating a dataset of 1,000 simulations. The design tasks and the agents' knowledge and properties were randomly generated at the start of each simulation. Thus, the simulations are mutually independent, i.e., every simulation pair differs in both tasks and the agents. For each simulation, details of the simulation duration, agent communication, and agents' mental models were recorded. In particular, for every structure the agents generated, the data of the structure's properties was extracted: the associated network was stored (enabling calculation of network metrics such as density, degree centrality or clustering coefficient), and the information on structures used to derive the structure at hand was collected. In addition, the first occurrence in the agents' mental models (i.e., the structure's creation time stamp), as well as whether and when the structure first appeared in the conversation, were extracted. Such a dataset enables tracking the change in the cumulative number of structures the agents generated and communicated, thus depicting the design solution space expansion.

3 RESULTS

The changes in the cumulative number of structures the agents generated are presented in Figure 2a and the cumulative number of structures the agents mentioned is shown in Figure 2b. The figures show the data averaged over all simulations. The simulation durations were normalised and, for each simulation, a percentage of the overall number of structures generated and communicated was tracked as the simulation progressed. Such a transformation preserves the expansion trends and enables comparison among simulations. The average trends and the standard deviations of simulation data are presented in Figure 2.

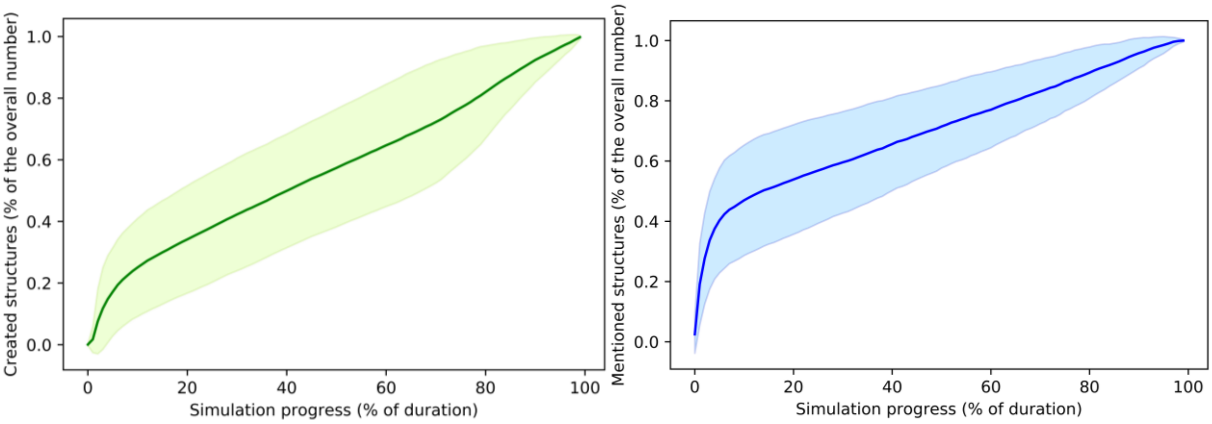

Figure 2. Simulated design solution space expansion: a) the cumulative number of newly generated structures, and b) the cumulative number of communicated structures (averaged over all simulations, standard deviation shown in lighter colour)

The data were further studied to determine if particular classes of simulated trends emerged. The previously described transformations enabled representing each simulation as a 100-dimensional vector capturing the change in percentage of the overall number of mentioned structures. The analysis of such data (using silhouette score, as well as the elbow method) indicates the existence of four classes of trends, classes A, B, C and D. K-means clustering was used to classify the simulations, and the average trends in the cumulative number of mentioned structures for each category are presented in Figure 3.

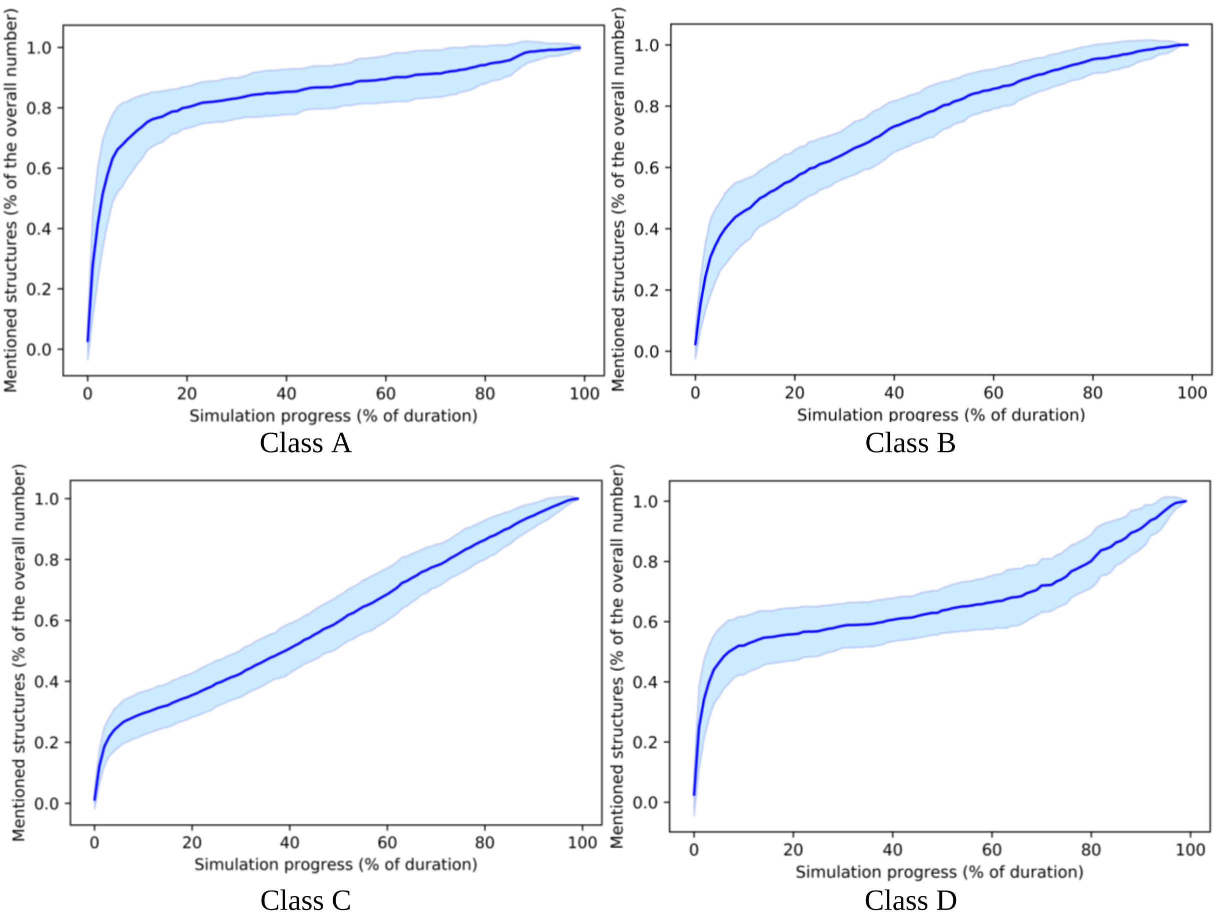

Figure 3. The cumulative number of communicated structures for each class of simulation

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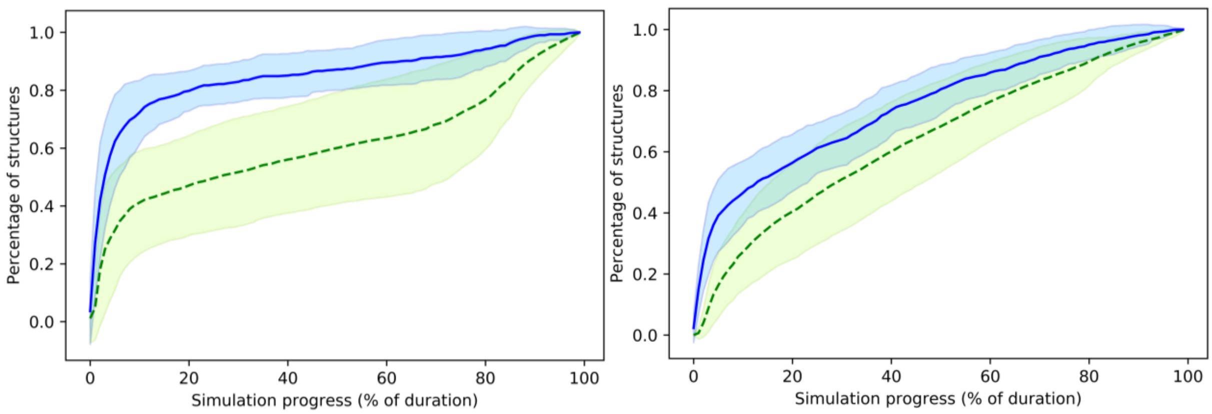
Since the data used in classification masks the information on the number of steps needed for convergence and omits the details on the actual size of the design space, it is interesting to observe if the classes differ in these characteristics. The average values and standard deviations of the simulation duration, the number of newly generated structures and the number of communicated structures for each class are presented in Table 1. The table also shows the average number of created and communicated structures that are feasible solutions (i.e., satisfy the task requirements) per simulation run. The data permits characterizing each simulation run using additional properties such as the process entropy, differences in generated structures' properties (i.e., novelty calculation), PS index, or turn-taking among agents and the speakers' dominance. However, here we only report the differences in the convergence speed and in the number of generated and communicated structures and solutions.
The differences among classes were tested using ANOVA and Kruskal-Wallis tests (depending on whether the normality assumption was violated). The subsequent pairwise comparisons were performed using Tukey test and Wilcoxon rank sum test with Holm correction. For space limitations, only the cases where one class was significantly different from all the others are marked.

Table 1. Statistics for each class (average value and standard deviation)

Class	**Class A**	**Class B**	**Class C**	**Class D**
Class size	209	262	356	173
Simulation duration (SD)	552.90 (251.70)	427.10* (193.25)	638.11 (181.78)	645.62 (228.01)
Created structures (SD)	131.90* (64.64)	203.90 (87.87)	329.62* (90.01)	190.43 (84.91)
Mentioned structures (SD)	12.83 (3.27)	16.44 (4.63)	24.83* (7.28)	15.24 (4.04)
Created solutions (SD)	4.85 (8.83)	13.79 (23.39)	36.67* (36.99)	16.95 (18.55)
Mentioned solutions (SD)	1.37* (0.72)	3.517 (2.48)	7.53* (4.61)	3.85 (2.37)

* class different from every other class at the significance level of $p < 0.05$

Finally, the trends in the cumulative number of communicated structures are contrasted with the corresponding cognitive effort in generating new structures, i.e., to trends in the cumulative number of newly generated structures. Figure 4 provides the details on the average change in the cumulative number of newly generated structures for each class.



Class A

Class B

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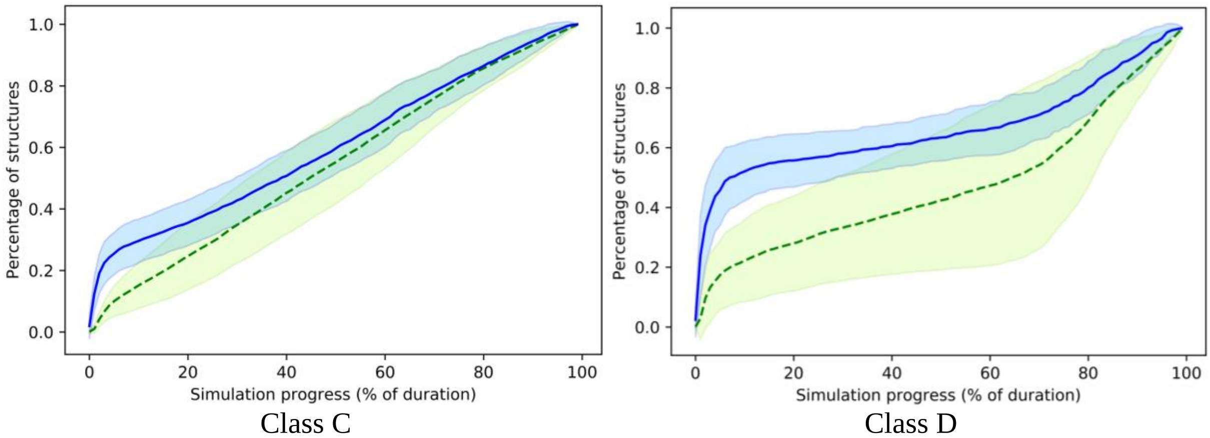

Figure 4. The comparison of trends in the cumulative number of newly created structures and the cumulative number of communicated structures for each class (green dashed line represents the cumulative number of new structures added to the agents' mental models, blue line represents the cumulative number of communicated structures)

4 DISUCUSSION

As seen in Figure 2, the simulated teams, on average, first list several structures at the simulation start and then proceed to introduce new structures into the conversation at the constant rate until the solution is found and simulation terminates. While the linear trend in a change of the cumulative number of communicated structures observed as the simulation proceeds matches the findings of the empirical studies reported in (Gero, Kannengiesser and Pourmohamadi, 2014; Gero, Kannengiesser and Williams, 2014; Kannengiesser et al., 2015), the significant number of structures communicated at the session start does not correspond to the empirical findings. The reason for such discrepancy lies in the simulation setup where each agent has a well-grounded portion of knowledge that likely overlaps with the task requirements. The agents, thus, recognise several relevant function nodes and are able to traverse the links to reach the structure space quickly. As evidenced by the graph in Figure 2a, the structures communicated at the session start are not newly created. Instead, the agents are reusing the existing knowledge to introduce the structures that, at first hand, seem relevant. Since none of the structures known to the agents at the simulation start satisfies all of the requirements, the agents then proceed to explore the structure space in search of a suitable solution. In doing so, the agents introduce new potential solutions at a constant rate.

The consistent rate at which the solutions are generated in the agents' mental models (Figure 2a) accords with empirical studies (Kan and Gero, 2016; 2017) suggesting that the cognitive effort directed at the structure space expansion remains constant throughout a design session. Rather than shifting to the solution space only after the problem space has been set, the agents rely on the solution-related issues to inform the problem framing (and vice-versa) from the session start. These findings are well-aligned with the principles of the co-evolution model of design.

A more in-depth study of the dataset revealed that the simulations could be classified as belonging to one of the four regimes depicted in Figure 3. Of these classes, the most common one, *Class C*, shows a more linear trend than that obtained by averaging over all simulations. The simulations falling in this class closely match the empirical results reported in the literature, demonstrating that the cognitive processes implemented are sufficient to generate trends observed in the real world. Nevertheless, the remaining classes offer several interesting insights as well. The four classes are discussed:

1. The first class, denoted as *Class A,* is characterised by an initial period where several structures are introduced, followed by a period of stagnation in design structure space expansion: only a few new structures are added to the conversation in the later periods. The inspection of the data revealed that the simulations in this class correspond to tasks for which the solutions are scarce and modifying a (partial) solution using union or concatenation mechanisms leads to a structure that no longer satisfies the requirements. In such a setting, the agents are progressing very slowly. The majority of newly generated structures get immediately dismissed as unsatisfactory and are, thus, not communicated to the team. Instead, the agents discuss the function and behaviour issues, since those remain consistently active in their mental models. As a result of this dynamic,

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the number of communicated structures remains mostly unchanged. However, once a suitable solution is detected, the agents quickly converge to this solution. Namely, the long period of discussing the problem-related issues enables the agents to develop similar views on the requirements. Once a solution is proposed, the agents quickly recognise its suitability and converge.

2. The second class, *Class B*, is characterised by a pattern of structure occurrence that follows a logarithmic function. In addition, this simulation class contains the shortest simulations, i.e., the tasks for which the agents converged quickly. The typical case falling in this category is the one where several partial solutions (i.e., meeting most, but not all, of the requirements) are known to the agents at the simulation start and modifying them generates new partial solutions. These partial solutions remain sufficiently active throughout the simulation, thus creating a basis upon which the agents expand the solution space. However, despite a relatively large number of generated structures, the structures rarely satisfy all the requirements. Thus, once an agent generates a suitable structure, this structure remains the most active in its mental model (i.e., the agent becomes fixated) and continuously shares this structure with others. After some time, the rest of the agents focus on the proposed structure, and the team eventually accepts it as a solution.
3. The third class, *Class C*, is the one where the agents know several partial solutions and modifying them does not disturb the network properties upon which the requirements are posed. In contrast to *Class A*, the newly generated structures in this setting do not get dismissed but are reused and built upon to generate additional structures. Over the course of the simulations, the agents create many structures and manage to find several suitable solutions. However, the larger number of solutions prolongs the time needed for convergence as each agent has their solution candidate(s).
4. The fourth class, *Class D*, exhibits a trend in the solution space expansion that resembles a cubic function. In other words, the fourth class is characterised by a period of stagnation in solution space expansion occurring at the beginning or in the middle of a design session. Inspection of the data revealed that such pattern commonly results from several agents having insufficient knowledge about the task requirements, thus halting their progress past the initial guesses. Throughout the simulation, the agents slowly learn about the problem or rely on a more knowledgeable (i.e., expert) agent to provide links that would describe the requirements and enable reaching the solution space. While new structures can be generated during this process, the links connecting structures to relevant behaviour nodes are not sufficiently grounded. Thus, the most active knowledge elements in agents' mental models remain those related to the problem space. Accordingly, during this session period, the agents discuss the problem rather than the solution. Once the problem is sufficiently understood, the agents start revising the past structures and introducing new ones, until they finally converge.

The results in Table 1 demonstrate the magnitude of differences among the classes. For example, the simulations in *Class A* have a significantly smaller number of created structures and mentioned solutions than simulations in any other class. The mean number of mentioned solutions is slightly above one, showing that in numerous instances the agents accepted the first (and only) solution they encountered. On the opposite end of the spectrum regarding the number of communicated and generated structures (and solutions) is *Class C*. The simulations in this class contained, on average, more than a double the number of generated solutions than the simulations in other classes. These results indicate that the design processes following the patterns displayed by the simulations in *Class C* have the highest probability of resulting in creative outcomes. However, the data also demonstrate that generating a large number of suitable structures may significantly delay the convergence.

Finally, one can discuss the relation among the cognitive effort - measured through the number of newly generated structures - and the cumulative number of communicated structures. Kan and Gero (2017) used the cumulative number of communicated structures as a proxy for cognitive effort, assuming that the two followed a similar pattern. While these assumptions hold for the majority of simulated cases, Figure 4 demonstrates that several instances in *Classes A* and *D* deviate from this assumption. Namely, while the corresponding cumulative graphs of the structure occurrences imply no cognitive effort directed at structure space expansion, the cumulative graphs of the newly generated structures in both cases show that new structures are being created. These structures are deemed inadequate in the context of the task at hand or are insufficiently active to be mentioned in the communication. Thus, the agents opt not to share them with others.

Table 2 summarizes the discussion by describing a typical simulation from each of the classes.

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Table 2. Summary describing a typical simulation in each class

	Simulation properties	Team behaviour	Outcomes
Class A	- Building on partial solutions results in structures not satisfying any requirements - Scarce solutions available	- Newly generated structures dismissed and not reused - Small number of structures communicated - Quick acceptance of the proposed solution	- Logarithmic cumulative structure occurrence - Very small number of solutions - Moderately quick convergence
Class B	-Building on partial solutions results in other partial solutions but rarely leads to solutions	- Agents build on the generated partial solutions - Agent(s) fixate(s) one solution and persuade(s) others to accept it	- Logarithmic cumulative structure occurrence - Moderately high number of solutions -Quick convergence
Class C	- Building on partial solutions preserves properties relevant to the task - Large number of solutions available	- New structures generated at a constant rate (building on partial solutions) - A large number of solution candidates proposed	- Linear cumulative structure occurrence - Large number of solutions - Slow convergence
Class D	- Similar to C but there is a mismatch between agents' knowledge and task requirements	- A long period dedicated to problem discussion (due to incomplete knowledge)	- Cumulative structure occurrence resembles a cubic function - Slow convergence

5 CONCLUSION

This work utilised computational agent-based simulations to explore the trends in the design solution space expansion in teams. The results demonstrate that cognitive mechanisms implemented in the agents are sufficient for the emergence of a linear trend in a cumulative structure occurrence, agreeing with the empirical findings. Similar to real-world studies, the simulated team's cognitive effort in exploring and expanding the solution space remains constant throughout a design session.

To further the study of team solution space expansion, the simulated sessions were inspected to detect classes of emerging patterns. The analysis resulted in the detection of four distinct solution space expansion regimes displayed by the simulated teams. Further studies should explore whether the regimes occur in the empirical data, and simulations can be utilised to suggest approaches that mitigate the difficulties in solution space expansion observed in several classes.

The computational model can be improved in several ways to further the study of solution space expansion. Namely, the results revealed a discrepancy with the empirical data in the agents' behaviour at the session start. Also, the task-generating algorithm should be refined, and agents should be equipped with additional problem-solving strategies and mechanisms for structure generation. Currently, tasks are created randomly, sometimes resulting in tasks unsolvable using the existing solution-generating mechanisms.

The detail data on the structure space and the agents' cognitive behaviour provide numerous avenues for future research. For example, the future work will explore the link among the solution space expansion and the novelty of the generated solutions, informing creativity studies. Similarly, the data on the individual cognitive behaviour can be contrasted to that displayed at the team level to gain deeper insights into the emergence of team-level phenomena.

ACKNOWLEDGMENTS

This work is funded by Ministry of Science, Education and Sports of the Republic of Croatia, and Croatian Science Foundation project IP-2018-01-7269: Team Adaptability for Innovation-Oriented Product Development - TAIDE (http://www.taide.org), and has been supported in part by the US National Science Foundation under grant numbers CMMI-1400466 and CMMI-1762415 to John Gero. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of US National Science Foundation.

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https://doi.org/10.1017/pds.2021.69 Published online by Cambridge University Press