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Effect of team diversity on teams' design space: a computational approach

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Abstract
Understanding team diversity has become essential for modern-day organisations. This study explores the impact of knowledge diversity in design teams through computational simulations. By analysing design space characteristics, we study how diverse teams perform compared to less diverse counterparts. Results reveal that highly diverse teams exhibit increased efficiency, quicker convergence, and larger but sparser design spaces. This work contributes to understanding the impact of knowledge diversity in design teams and sets the stage for future systematic studies of diversity.

Keywords: design teams, design cognition, team diversity, design space, agent-based modelling

1. Introduction
The emergence and increased prominence of multicultural, multinational, and interdisciplinary teams have brought team diversity into the research spotlight. Since early studies and theories, researchers have advocated assembling diverse teams, highlighting their potential to leverage their members' differences and generate creative solutions (Bodla *et al.*, 2018). On the other hand, numerous studies have found that team diversity may result in prolonged task completion time due to a lack of trust, an increase in conflicts, and coordination issues among team members (Patrício and Franco, 2022). Thus, it is not surprising that diversity is often seen as a 'double-edged sword' (Bodla *et al.*, 2018; Horwitz and Horwitz, 2007).
Studies of team diversity have yielded mixed results (Horwitz and Horwitz, 2007; Usher and Barak, 2020). One of the reasons for an apparent discrepancy in findings may lie in the complexity and multi-dimensionality of the "diversity" construct. Researchers emphasise that diversity covers all dimensions (i.e., attributes) along which individuals can perceive each other as different (van Knippenberg *et al.*, 2004). It spans dimensions broadly classified as bio-demographic and task-related (Hundschell *et al.*, 2022; Usher and Barak, 2020). Bio-demographic diversity covers innate and observable attributes such as age or ethnicity, whereas task-related diversity spans those attributes that relate to the task context (e.g., expertise or functional and educational background). Early studies of diversity indicated that task-related diversity positively impacts team performance, while bio-demographic diversity either had a negative effect or no influence over team performance (Horwitz and Horwitz, 2007). Nevertheless, more recent research yielded inconsistent findings even among studies with a fixed diversity type (e.g., task-related knowledge), team performance metric (e.g., creativity or efficacy), and study level (i.e., individual, team or organisational) (Hundschell *et al.*, 2022).
van Knippenberg et al. (2004) called for abandoning the idea that a particular diversity dimension has a consistently positive (or negative) influence on team performance, arguing that all dimensions could

have both positive and negative effects, depending on the interplay of the related processes and other diversity dimensions. The authors (van Knippenberg *et al.*, 2004) emphasise that negative social categorisation and positive information-elaboration processes intertwine within a team, steering the influences of particular diversity dimensions.

Given these complexities, studying diversity presents a challenge. Nevertheless, there is an imperative to do so (Menold and Jablokow, 2019), and - to understand the influence of diversity - we must first understand its different types (Bodla *et al.*, 2018), capturing their dynamic nature and quantitatively assessing their impact (Hundschell *et al.*, 2022). Computational simulations present a valuable approach for supporting and complementing empirical studies, as they guide our intuition and offer potential explanations of the mechanisms underlying phenomena observed in the real world. They allow us to isolate, manipulate and measure team properties or processes, systematically examining their impact on team performance and behaviour. Simulations were, for example, utilised by Lapp et al. (2019) to explore the impact of diversity in problem-solving styles on team performance.

By focusing on a single diversity dimension, this work presents a first step in an extensive study of the impact of diversity on design performance. We focus on the impact of knowledge diversity in a design team since such task-related diversity is considered a critical diversity dimension impacting non-routine design activities (Hoisl *et al.*, 2017). We aim to explore the influence of diversity in the knowledge of the members of a design team on the design space constructed during a simulated task. By tracking the design space size, density and entropy, this research sheds light on some of the main effects of knowledge diversity in design. The findings complement the existing empirical studies and form a basis for future, more complex studies.

The remainder of this paper is structured as follows. Section 2 presents a brief overview of the studies on knowledge diversity in design. The computational model and the experiments are described in Section 3, while the results are presented in Section 4. These results are discussed in Section 5. Finally, Section 6 concludes the paper with an outlook on future work.

2. Research background

Knowledge diversity refers to differences in team members' knowledge, perspectives, expertise areas, backgrounds, and skills (Zelaya-Zamora and Senoo, 2013). Numerous published works advocate for such diversity, claiming that a plurality of knowledge and perspectives is necessary for tackling complex tasks such as design (van Knippenberg and Mell, 2016). Multiple design studies employed multidisciplinary, transdisciplinary, and interdisciplinary teams (Nguyen and Mougenot, 2022), comprising members with diverse educational backgrounds (Dahlin *et al.*, 2005), levels of design education (Ou *et al.*, 2023), and professional experience (Kiernan *et al.*, 2020). Although a recent review paper (Nguyen and Mougenot, 2022) argues that most of these studies employ de facto homogeneous teams (as recruited participants had a background in similar, creativity-related disciplines), the studies yield ample evidence that team diversity positively correlates with finding useful and novel (i.e., creative) solutions. Indeed, team diversity has been frequently linked to creativity (Bodla *et al.*, 2018; Christensen and Ball, 2016; Ou *et al.*, 2023; Park *et al.*, 2018). Diverse teams were found to explore a larger design space, discussing a broader range of topics and generating a larger number of potential solutions (Gero and Milovanovic, 2023). Consequently, such teams encounter numerous opportunities for idea cross-fertilisation as individuals pick other's solutions and refine them in accordance with their perspectives (Hoisl *et al.*, 2017). The diversity of knowledge enables team members to assess each solution from various perspectives (Menold and Jablokow, 2019), promoting a comprehensive evaluation and ensuring usefulness. Overall, these processes yield a rich design space, offering opportunities to generate creative designs. It is, thus, not surprising to find frequent calls for fostering diversity to avoid groupthink (Badke-Schaub *et al.*, 2007, 2010; Bodla *et al.*, 2018).

The other side of the coin relates to cognitive conflicts and communication load in diverse design teams. While similar team members possess a shared understanding of the requirements and potential solutions, diverse members must make an effort to effectively communicate their perspectives in order for the team to reach a consensus (Badke-Schaub *et al.*, 2007; Menold and Jablokow, 2019). Conflict in diverse teams has been labelled "unavoidable" (Badke-Schaub *et al.*, 2010), and several studies found diversity decreases team cohesion (Aggarwal and Woolley, 2019; Menold and Jablokow, 2019). These

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studies found that too much diversity hampers performance, especially in environments that require high shared understanding and quick coordination (Hoisl *et al.*, 2017). Nevertheless, if the team members manage to turn obstacles such as cognitive conflicts into stimulating experiences while avoiding affective conflicts (Badke-Schaub *et al.*, 2010), they will learn and, consequently, benefit from their differences through intense communication (Frigotto and Rossi, 2012).

3. Methods

Building on the theoretical foundation presented in the previous section, one can formulate several hypotheses regarding the effect of knowledge diversity on team performance and the design space explored by the team. Within this work, we utilise a computational system to simulate a design team and study if the observed trends align with the expectations. In doing so, a two-fold goal is achieved: we test the system, verifying its soundness, and obtain a basis for future systematic studies on diversity by establishing sufficient conditions for the emergence of the phenomena of interest. The system is described in detail in (Perišić, 2020) and has previously been employed in studies of various team behaviours and processes (Perišić et al., 2019a, 2019b, 2021, 2023).

3.1. Designers as agents

The computational system represents designers as cognitively rich agents working towards a shared goal. Each agent's knowledge is modelled as a network whose nodes correspond to functions, behaviours, and structures (Gero, 1990). The spreading activation algorithm is implemented to simulate designers' attention shifting from one design issue to another through formulation, synthesis, analysis, evaluation, and reformulation I, II and III processes (Gero, 1990). The effort required to shift from one node to another (i.e., process a particular link between the nodes and spread activation over it) depends on the agent's previous experiences. As a link gets more frequently used, it becomes grounded and, thus, easier to process as the activation spreads over it at virtually no cost (Kahneman, 2011). This mechanism enables conceptualising the agent's expertise as a well-grounded, dense subnetwork of its knowledge.

Several abstractions and simplifications have been made to facilitate simulations. Rather than representing a specific real-world structure, each structure node in agents' mental models corresponds to an undirected network. Each behaviour node corresponds to a specific network property (e.g., having the clustering coefficient above a certain threshold). The design task is conceptualised as a set of requirements imposed on the network properties that a structure (i.e., a network) must display to be accepted as a solution. The task relates to the required behaviours, and the agents must construct a structure whose corresponding network displays the necessary properties. While exploring the design space, the agents can generate new structures by combining or modifying the known ones, potentially creating structures that exhibit a previously unseen combination of behaviours.

Collaboration among agents is enabled through communication of the relevant design issues and processes. Whenever a knowledge link and the corresponding nodes receive sufficient activation in one agent's mental model, the agent can decide whether to communicate these knowledge elements to their peers. Such communication impacts the cognitive processes of the listening agents as they learn (or further ground) the communicated links and direct a portion of their attention to the relevant nodes. Throughout the simulation, agents elaborate on their knowledge of relevant issues to find a suitable structure. Once a potential solution is found and communicated by one member, all agents must ensure its suitability by grounding the links to the required behaviour nodes. If successful, the simulation is terminated. In other cases, the increased probability of failure due to insufficient progress might impact the agents, who then direct more attention to the structure space, re-evaluate previously communicated structures, and propose partial solutions to enhance their chances of success (Stempfle and Badke-Schaub, 2002). More on the affective, collaborative, and cognitive aspects implemented in these agents can be found in (Perišić, 2020).

3.2. Design space representation and metrics

Since this work aims to study the effect of knowledge diversity in a design team on the resulting design space, a convenient approach is required to represent and measure various aspects of the design space.

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One approach found in the literature (Gero and Milovanovic, 2022) advocates representing a design space as a network of design issues or concepts. Those authors describe how network nodes and links among them can be extracted from the communication among designers in empirical studies. Similar approaches that require tracking utterances to draw and analyse the design spaces have been employed in various empirical studies (Ensici *et al.*, 2013). Building on these works, we develop a design space representation based on communication among agents. Each communicated design issue corresponds to a particular node, and a link among nodes is created if the nodes are both mentioned within a window of two simulation steps.

The network representation of a design space enables measuring several properties identified as important based on the works reviewed in Section 2. One such metric is network size, which informs us of the number of discussed design issues. A complementary metric relates to network density, as a dense network implies frequent elaborations and knowledge sharing (Rahmi and Indarti, 2019). Finally, we extract network entropy, as previous studies have linked the increase in entropy of design space to an increase in creative potential (Kan and Gero, 2018; Krus, 2015).

3.3. Simulation setup

Within this work, we associate the agent's expertise with a particular set of behaviour nodes. We assign a set of five behaviour nodes to each agent as their expertise. In the agent's mental model, these behaviour nodes are tied to a rich set of functions and structures, forming a dense, well-grounded subnetwork and enabling the agent to quickly recall design issues associated with the behaviours in its expertise. Building on this, we implement knowledge diversity among team members as a degree of overlap among their expertise areas. In a highly diverse team, there is no overlap in their expertise (i.e., associated behaviour nodes). A similar team with no diversity is comprised of agents with the exact same area of expertise. In this way, team members' knowledge diversity corresponds to a range of knowledge components available for use and recombination (Wen et al., 2021). This design permits an overlap in agents' (overall) knowledge even in cases when there is no overlap in their expertise areas. In other words, a design issue within one agent's expertise area can be present in the mental models of their teammates, but its respective links will be loose and require significant effort to process.

Simulations were run on a set of 1000 tasks, each performed by six teams with distinct knowledge overlap levels (ranging from no overlap to a setting where all agents had precisely the same set of five behaviour nodes in their expertise). To ensure direct commensurability, in all scenarios, each agent's mental model at the simulation start comprised the same number of design issues and links among them. All other simulation settings remained the same between the simulated scenarios to isolate the effect of team diversity. The maximum number of simulation steps was set to 1000.

4. Results

The success rates (i.e., the percentage of tasks in which simulated teams managed to find and agree upon a suitable structure within the given number of simulated steps) increased significantly with the increase in diversity. In the six simulated settings with varying percentages of shared expertise areas among members (0%, 20%, 40%, 60%, 80% and 100%), the success rates were 72.5%, 63%, 57.3%, 39.3%, 32%, and 13.4%, respectively. When considering only the successful runs, the most diverse teams converged faster than their more similar counterparts. The average number of steps for convergence for the varying percentages of shared expertise areas were as follows: 388.72, 450.75, 511.756, 596.75, 649.17, 748.41.

The change in the size of the design space (i.e., the number of distinct design issues communicated) was tracked throughout each simulation. Figure 1(a) presents the distributions of the design space size at the simulation end, and Figure 1(b) presents the change in the size of the design space over time for each simulation setting. The statistical significance of differences among the distributions in Figure 1(a) was tested using Welch ANOVA, followed by the pairwise Welch t-test with Holm correction. Statistically significant differences ($\alpha = 0.05$) were found among all settings except between the settings in where there was a 60% and 40% overlap among team members' expertise areas.

We tracked the density of the explored design space. The distribution of densities of the final (i.e., at the simulation end) design spaces is presented in Figure 2(a). Significant differences ($\alpha = 0.05$) were found among all simulated settings. To observe how density changes over time, we employed the moving window technique using a window of 100 steps. The average values and standard deviations for each setting are presented in Figure 2(b).

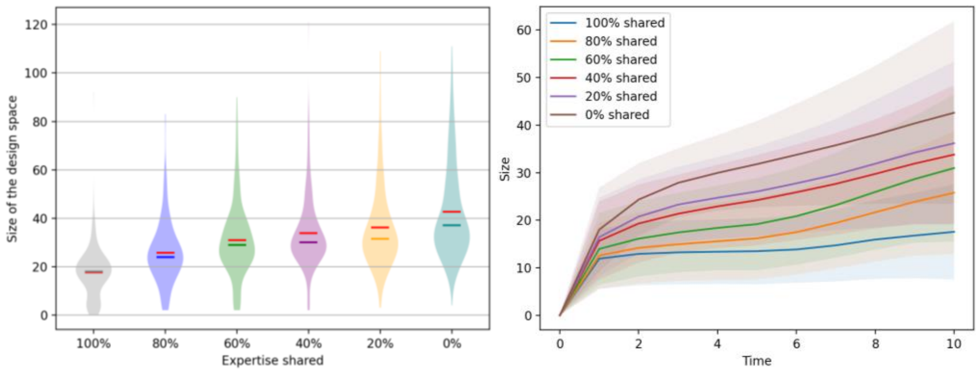


Figure 1. Size of the design space (a) overall (mean values marked in red); (b) over time (average and standard deviation at each simulation decile)

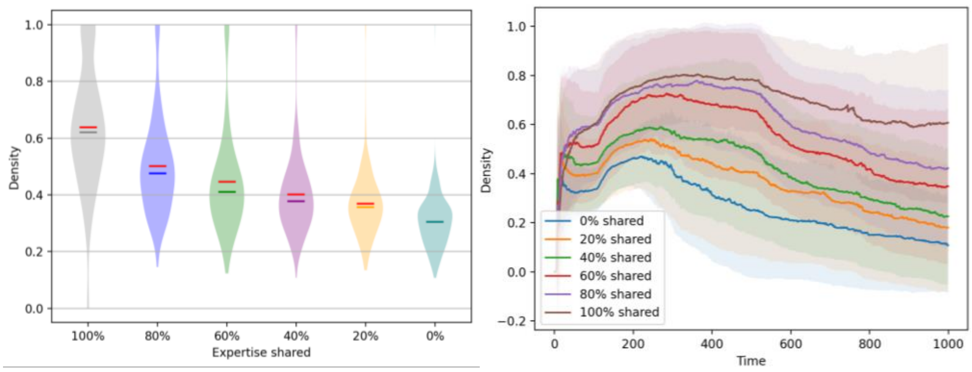
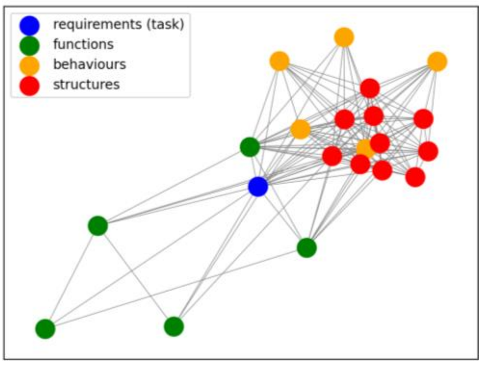
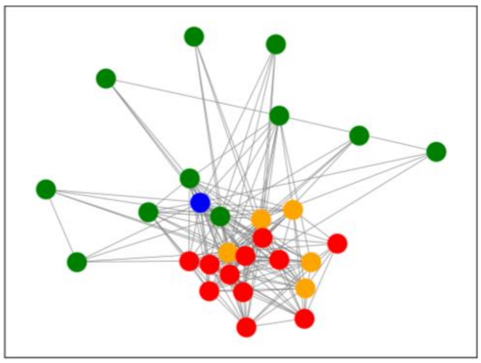


Figure 2. Density values (a) overall (mean values marked in red); (b) dynamic density using the moving window technique (average and standard deviation shown)

To gain further insights into their differences, we selected one simulation run from each simulated setting and studied the corresponding (final) design spaces shown as force graphs in Figure 3. The simulations were chosen based on the average density values. Specifically, to identify the most representative simulation runs, we picked those whose final design space density was closest to the simulation setting's mean. As the diversity increases, the number of different structures generated increases (shown in red in Figure 3). In addition, the structures are clustered together less.



(a) 100% shared



(b) 80% shared

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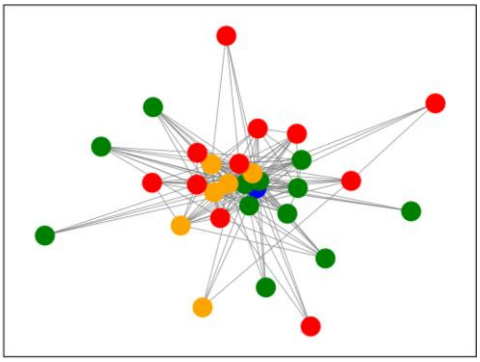
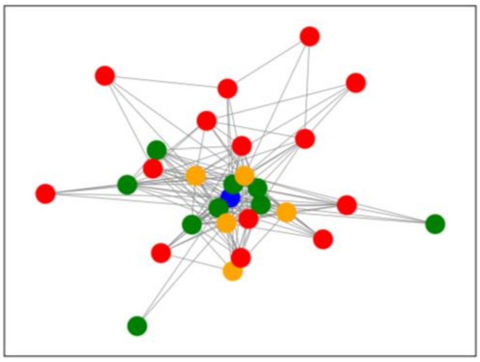
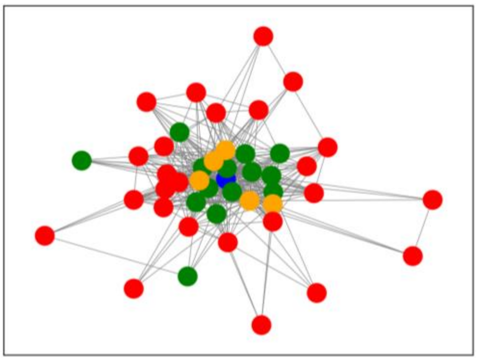


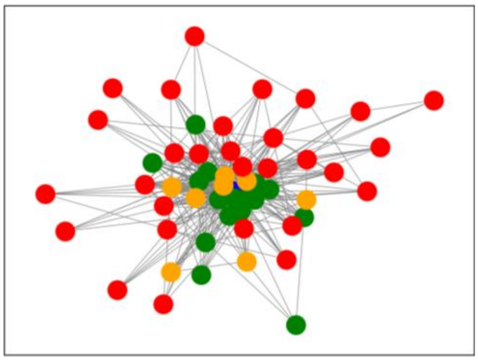
(c) 60% shared



(d) 40% shared



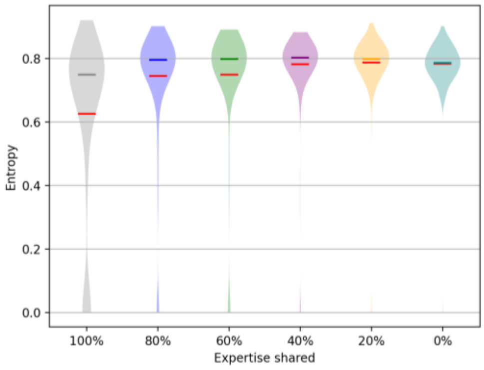
(e) 20% shared



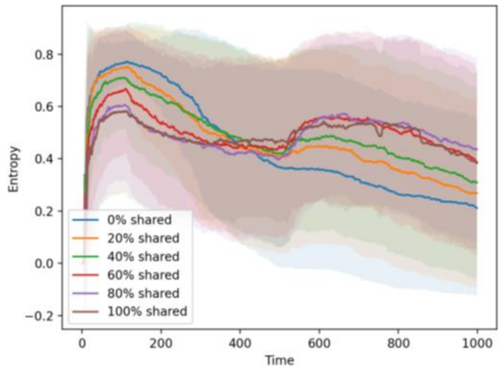
(f) 0% shared

Figure 3. Density of design spaces of the representative simulation run for each diversity setting

Finally, the design space entropy was measured in each simulation run (Figure 4). The distributions of the entropy at the end of the simulation are presented in Figure 4(a). Statistically significant differences were found between the least diverse team and all other settings, as well as between the "20% shared" setting and "60% shared" and "80% shared" settings. Figure 4(b) shows the dynamic entropy obtained by employing the moving window technique.



(a) Overall mean entropy



(b) Dynamic entropy

Figure 4. Design space entropy (a) overall (mean values marked in red); (b) dynamic entropy using the moving window technique (average and standard deviation shown)

5. Discussion

The studies summarised in Section 2 point to the potential benefits of employing a diverse design team. The results obtained in the current work corroborate these claims as diverse teams emerged as much more successful in finding solutions than their less diverse counterparts. Diverse teams are more efficient on average and converge to the solution quicker than less diverse teams. At first glance, this finding might seem counterintuitive, as the literature indicates that diversity imposes the need for

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discussions and postpones consensus (Hoisl *et al.*, 2017; van Knippenberg *et al.*, 2020). However, diverse teams have the advantage of having access to multiple perspectives and diverse expertise areas. As such, there is a higher probability that a generated task will significantly overlap (in terms of the required behaviours) with at least one member's expertise area (Hoisl *et al.*, 2017). These members are, thus, able to quickly produce high-quality (partial) solutions (Björklund, 2013) and can direct the search of their teammates, maintaining a low level of divergence (McComb *et al.*, 2015). Nevertheless, the data reveals that, in cases where a task has a high overlap with the less diverse teams' expertise area, they benefit from their similar mental models and converge quicker than the highly diverse teams.

Figure 1 shows how team diversity impacts the size of the generated design space, revealing a positive correlation. Empirical studies have concluded similarly, describing how individuals in diverse teams draw on their experiences to generate and explore a larger design space (Badke-Schaub *et al.*, 2010; Menold and Jablokow, 2019) and benefit from the variety of known structures, allowing them greater recombinant opportunity (Hoisl *et al.*, 2017). Teams continue to introduce new design issues and expand the design space throughout the simulation runs (Figure 1(b)). After the initial burst of the ideas and design issues, a linear increase is observed until the simulation ends. A similar trend was observed in several empirical studies (Gero and Kan, 2016; Martinec *et al.*, 2020).

The change in density of the design space with respect to the change in team diversity is shown in Figure 2. One can note a negative trend, demonstrating that greater diversity results in a sparser design space. Recalling that the relevant studies emphasise that the success of diverse teams necessarily depends on communication and discussions (van Knippenberg *et al.*, 2004), the opposite trend might have been expected. Namely, frequent elaborations and discussions of various viewpoints are required to reach consensus in diverse teams. In network terms, this implies that numerous design issues are likely to be interconnected as team members establish a shared understanding of the problem, consequently increasing the design space density. On the other hand, since the diverse teams explore larger design spaces in the same time frame as less diverse teams (Figure 1), lower density is not surprising.

We can study these differences further by comparing the design spaces from selected simulated runs (Figure 3). The graphs represent how increased diversity in design teams results in larger design spaces. The number of functions and behaviours discussed increases with the increase in diversity, but the most significant increase relates to the number of structures. In other words, diverse teams consider numerous structures, increasing their chances of finding a feasible solution. An interesting insight relates to the distribution of the link generated between design issues. The network depicting the design space explored by the least diverse team (Figure 3(a)) comprises numerous links linking the structures to one behaviour node, while function nodes mostly remain loosely connected to other nodes. Such distribution of links demonstrates that the team spent little time discussing the problem space, likely because their understanding of the related functions was similar due to the shared expertise. Instead, their communication centred around a couple of relevant behaviour nodes (those closest to their expertise), from which they tried synthesising potential solutions. In contrast, the network representing the design space explored by the most diverse team (Figure 3(f)) shows a tightly connected subnetwork of several functions, behaviours, and structures, while other structures remain on the outskirts of the network. This network layout indicates that diverse teams thoroughly discuss and interlink problem-related design issues (functions and behaviours) to establish a shared and comprehensive understanding of the problem at hand (Badke-Schaub *et al.*, 2007). They build on the derived understanding to propose potential solutions, but many of the structures mentioned get dismissed by others and are not further discussed. Studies have noted such behaviour is desirable, as dropping less promising ideas enables utilising the full potential of team diversity when striving to generate creative solutions (Badke-Schaub *et al.*, 2010). We can link these results to the trends observed in Figure 2(b). One can observe how, in all simulation settings except the least diverse one, there is a drop in density in the initial stages of the simulation. This drop occurs as each agent draws on their expertise to communicate design issues they deem important for the task. Introducing many different design issues in a short period decreases the network density. Then, a period of density increase is observed as the agents discuss the potential links among the introduced design issues. Following this period, the agents start introducing and discussing potential solutions, decreasing the network density. These new design issues are introduced until the simulation ends (as corroborated by Figure 1(b)), despite the teams' inclination to converge.

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Finally, we consider the design space entropy (Figure 4). Figure 4(b) shows that, in all settings, the first half of the simulation is marked with an increase and subsequent decrease in entropy. The increase in entropy results from the initial increase in the design space size (Figures 1(b) and 2(b)) and indicates a divergent period of the simulation. As the agents start focusing on a specific subset of the design space, entropy starts to decrease. Nevertheless, in the second half of the simulation run, one can note differences among the settings. Namely, the entropy continues to decrease for highly diverse teams, while in settings comprising less diverse teams, the entropy increases. These trends result from the team's perceived success. Highly diverse teams often find several potential (partial) solutions early on and spend the rest of the simulation refining these structures until a solution is found and agreed upon. McComb et al. (2015) observed similar behaviour in their work, noting that successful teams quickly and accurately classify problems, upon which they begin moving towards a solution in a balanced search with minimal levels of divergence. In contrast, less diverse teams lack the expertise and knowledge to generate high-quality (partial) solutions quickly. Therefore, as time passes, they are faced with an increased probability of failure, prompting them to broaden their search by revisiting previously communicated design issues and trying to recombine them to advance (Stempfle and Badke-Schaub, 2002). This behaviour increases entropy, indicating an increase in divergence in the team.

These dynamics yield design spaces whose average entropies are shown in Figure 4(a). Although the highest dynamic entropy is achieved by the most diverse teams at the initial stages of the simulation, their subsequent narrow search results in a final design space whose entropy is, on average, lower than that of the teams with a knowledge overlap (20% and 40%). According to Kan and Gero (2018), such high entropy indicates a high creativity potential. Future studies will take a closer look into the generated structures to test this hypothesis further.

6. Conclusion

This work builds on the research works that express a need for an accurate measurement of knowledge (Huang *et al.*, 2014) and a systematic study of the impact of (knowledge) diversity on team behaviour and performance (Bodla *et al.*, 2018). By tracking how design spaces change with a change in team diversity, we aim to complement empirical studies and shed light on the impact of knowledge diversity in design teams. While the results presented offer a potential explanation of the processes underlying the team dynamics observed in the real world, further empirical studies should validate these results.

Nevertheless, this study offers a first step in a comprehensive study of diversity. In order to learn how to fully leverage team diversity (Friis, 2015), we must study under which circumstances we can benefit from each diversity dimension and how to recognise, prevent or mitigate negative influences in cases when mediating and moderating processes render the diversity disadvantageous.

Future steps will include systematically adding other forms of diversity (both task-related and bio-demographic) and studying their mutual interplay. This will require incorporating the impact of two competing processes on the influence of diversity in design teams: social categorisation and information elaboration (van Knippenberg *et al.*, 2004). The system will enable studying a wide variety of relevant research questions, including that of the influence of diversity on creativity of the final solutions, knowledge sharing and integration (Men *et al.*, 2019), and team efficiency (Hoisl *et al.*, 2017). It is now possible to study the interplay of, for example, self-efficacy and diversity (Menold and Jablokow, 2019) or test under which circumstances knowledge diversity overpowers cognitive ability (Kokotovich and Dorst, 2016). Simulations offer an approach for structured studies of diversity.

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