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Article

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Does mental model similarity equal innovation team performance?

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Abstract

Purpose – This paper addresses challenges and opportunities of interdisciplinary teamwork in innovation management, focusing on how team mental models (TMMs) can foster more effective collaboration among team members from diverse backgrounds. The research examines the relationship between TMM similarity and team performance in interdisciplinary innovation teams.

Design/methodology/approach – An exploratory study was conducted with 55 participants across 15 teams. TMM similarity was measured by analyzing team interactions using a web-based interface that facilitated contrasted comparison ratings. These ratings were first processed into individual graphs via a shortest-node-finding pathfinder algorithm, then compared. Subject matter experts evaluated team performance.

Findings – The results reveal a significant positive correlation between TMM similarity and team performance in interdisciplinary innovation teams, suggesting that greater alignment in team members' mental models enhances overall innovation project performance.

Research limitations/implications – Although the academic programs sampled replicate the environment, challenges and various other aspects of innovation projects, they can only be considered proxies for innovation projects within real organizations. Further research within professional environments, using a larger sample, is recommended.

Practical implications – The findings highlight the value of assessing and fostering TMM similarity to improve teamwork and performance in interdisciplinary innovation projects. The interface and code used are publicly available to encourage their implementation in organizations.

Originality/value – This research provides novel insights into the application of TMMs within interdisciplinary innovation teams, extending the concept beyond its traditional use in unidisciplinary and structured task settings.

Keywords Innovation, Teams, Mental models, Interdisciplinary collaboration, Team performance, New product development

Paper type Research article

1. Introduction

Innovation provides organizations with a competitive edge and is essential for value creation and performance (Cho & Pucik, 2005; Rajapathirana & Hui, 2018; Saunila, Pekkola, & Ukko, 2014; Akman & Yilmaz, 2008). Innovative companies have higher levels of productivity and economic growth and a positive relation between an organization's overall performance and innovation (Cainelli, Evangelista, & Savona, 2004; Bowen *et al.*, 2010; Saunila *et al.*, 2014). At the same time, companies find themselves in a constantly changing world with increasing complexity (Du Plessis, 2007).

Teams need to continuously adapt to these conditions and learn as a team, which requires the continuous assessment of underlying mental models (Rupčić, 2022). This complexity increases further for teams that rely on digital technology to communicate and do their work (Müller, Schischke, Graf, & Antoni, 2023) or for teams that fully work remotely (Kirkman & Stoverink, 2021; Morisson-Smith & Ruiz, 2020). This affects organizations' demand for



corresponding innovation strategies, projects and teams (Blackwell, Wilson, Boulton, & Knell, 2009; Du Plessis, 2007) and how leaders influence the teams they are leading (Toader & Martin, 2023). The importance of interdisciplinary teams for innovation is continuously increasing (Edmondson & Nembhard, 2009; Su & Moaniba, 2017; Blindenbach-Driessen, 2014), especially when teams are frequently reorganized and have to find ways to quickly become a productive unit (Van Rensburg, Santos, & de Jong, 2023). In this context, cross-disciplinary knowledge is described as having a vital role in innovation (Shams, Vrontis, Weber, & Tsoukatos, 2018; Moaniba, Su, & Lee, 2018).

Interdisciplinarity contributes to innovation with several factors, as outlined, for example, by Alves, Marques, Saur, and Marques (2007), Fay, Borrill, Amir, Haward, and West (2006), Paletz and Schunn (2010), and Blackwell *et al.* (2009). These factors include a more extensive and responsive support structure and an increased possibility of accessing a wider range of knowledge. This encourages a more novel usage of said knowledge, leading to higher associated creativity and a higher possibility for radical ideas. But interdisciplinarity also has its downsides. They include a low superordinate identity, functional and time allocation diversity and multiple reporting relationships, which all can result in implications for team trust, task agreement, freedom to express doubts, collaborative communication and project complexity (Webber, 2002; Lovelace, Shapiro, & Weingart, 2001; Edmondson & Nembhard, 2009). A prevailing criticism is that team members with different backgrounds perform worse than homogeneous teams because they fail to “talk the same language”.

This paper argues that team mental models (TMMs) represent this notion of “talking the same language”, as they are defined as “team members’ shared, organized understanding and mental representation of knowledge about key elements of the team’s relevant environment” (Mohammed, Ferzandi, & Hamilton, 2010, p. 879). So far, most studies have examined how similar this understanding and these mental representations are. A common assumption is that TMMs may serve as indicators of how effective and high-performing a team will be (Mohammed *et al.*, 2010; Klimoski & Mohammed, 1994) and provide a valuable angle for investigating how complex problems are solved within innovation teams (Badke-Schaub & Frankenberger, 2004).

2. Theoretical background and related work

2.1 Team mental models

TMMs provide a structured mechanism to map expertise and develop shared understanding. By fostering trust and team cohesion early and reducing cognitive load, TMMs enable boundary-spanning communication, enhancing collaboration and facilitating innovative problem-solving by ensuring that diverse contributions are accessible and meaningfully synthesized (Davison & Blackman, 2005; Casakin & Badke-Schaub, 2015).

Rouse, Cannon-Bowers, and Salas (1992) suggest that team members have a variety of TMMs simultaneously, and all categories can be more or less shared independently. Neumann, Badke-Schaub, and Lauche (2006) propose that TMMs in the context of innovation can be split into five categories: *task*, *process*, *team*, *competence* and *context*. The *team* category can be further divided into *team* and *team interaction*, making it six categories total. It describes team members’ knowledge about other team members: their abilities and characteristics (*team*), as well as their ideal level of teamwork (*team interaction*, e.g. having an appointed leader or not). The *task* category reflects the knowledge a team member has about a specific task. *Process* focuses on how tasks are generally approached (e.g. by having a leadership decision or an open discussion). *Competence* refers to how confident team members are in fulfilling a task. *Context* describes the surroundings (e.g. work in a large organization or a small startup).

2.2 Team mental model properties

[Badke-Schaub and Frankenberger \(2004\)](#) illustrate that TMMs usually have three distinct properties: *similarity*, *accuracy* and *importance*. *Similarity* refers to the degree of shared knowledge within a team. This is the prevalent property in TMM research, where *shared knowledge* is generally defined as how consistent or overlapping the individual team member's mental models are to each other ([Converse, Cannon-Bowers, & Salas, 1993](#); [Mohammed et al., 2010](#)). *Accuracy* is often measured by obtaining an "expert" mental model (e.g. [Lim & Klein, 2006](#); [Riemer & Schrader, 2016](#)). This is then compared to the mental models of the individuals and/or the team. The more convergent the models are, the more accurate the mental models of the non-experts are. *Importance* identifies the central attributes of a task. A central attribute in the context of mental models is defined as an attribute that is highly related to a lot of other attributes within a mental model ([Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000](#)).

2.3 Team mental models in interdisciplinary teams

As discussed in Chapter 2.1, TMMs are often split into six categories, and each TMM can have a total of three properties. Not all categories and properties have the same importance, and a high degree of one property does not necessarily equal better performance in interdisciplinary teams ([Badke-Schaub & Frankenberger, 2004](#)). The following paragraphs discuss all categories and properties, to limit the attention of this paper to only those most impactful to interdisciplinary teams.

[Mathieu et al. \(2005\)](#) as well as [Cooke et al. \(2000\)](#) explain that interdisciplinary teams often deal with innovative problem solving, where no single "right" solution or "most central" task exists. This suggests that a highly shared task mental model is not necessarily beneficial for performance in such teams. For this reason, the authors of this paper have excluded the *task* category. Next, *process* and *team interaction* are found to overlap conceptually. Definitions and examples provided by [Badke-Schaub, Neumann, Lauche, and Mohammed \(2007\)](#) (e.g. having a leadership decision or an open discussion) and [Mathieu et al. \(2000\)](#) (e.g. appointing a team leader or foregoing this decision) highlight their similarity. Therefore, this paper merged these two categories to form a broader category of *team interaction*, following the example of [Casakin and Badke-Schaub \(2015\)](#). The *competence* and *context* categories are treated as indirect factors. Competence, which reflects team members' confidence in task fulfillment, is argued by [Badke-Schaub et al. \(2007\)](#) to be a secondary category influenced by both team and task. Context, also referred to as environmental factors (e.g. [Langan-Fox, 2003](#); [Van den Bossche, Gijsselaers, Segers, Woltjer, & Kirschner, 2011](#)), pertains to external surroundings (e.g. large organizations or small startups) that influence TMMs indirectly rather than directly. These factors are therefore classified as secondary in importance, following previous research by [Casakin and Badke-Schaub \(2015\)](#). In summary, this paper prioritizes the *team* category, encompassing *team* and *team interaction*, as the central focus of analysis. For clarity, this combined category is referred to as TMM throughout the remainder of this paper.

Prior research also differentiated the three TMM properties: *accuracy*, *importance* and *similarity*. The properties of *accuracy* and *importance* are inherently linked to the *task* category, which this paper has excluded from the analysis. *Accuracy* reflects how precise a mental model is. However, in interdisciplinary TMMs, [Mathieu et al. \(2005\)](#) argue that constructing an accurate, or "expert", mental model is difficult because team members are encouraged to explore various new solutions, reducing the relevance of high *accuracy*. Similarly, *importance*, which measures the central attributes of tasks, is deprioritized as it is directly tied to the excluded *task* category. In contrast, *similarity* is identified as the most promising property for interdisciplinary TMMs. [Badke-Schaub and Frankenberger \(2004\)](#) emphasize its importance as well, and much of the existing literature suggests that a similar TMM contributes to better team performance (e.g. [Lim & Klein, 2006](#); [Mathieu et al., 2005](#); [Marks, Zaccaro, & Mathieu, 2000](#)). For these reasons, this study focuses on *similarity* as the primary property of interest.

2.4 Research hypothesis

Innovation is critical for an organization's success and an essential theme in business practice and related research. Interdisciplinary teams are assumed to have better success at producing genuinely innovative ideas, but also show inconsistent performance. A shared understanding of team and team interaction is assumed to correlate with higher performance in unilateral teams. It is generally assumed that this applies to interdisciplinary teams as well. This study sets out to investigate whether that is true. Hence, the following null hypothesis and alternative hypothesis are explored:

- H0.* In interdisciplinary teams tasked with creating innovation, TMM similarity and performance are not related.
- Ha.* In interdisciplinary teams tasked with creating innovation, TMM similarity and performance are positively related, where the higher the TMM similarity, the higher the team's innovation performance.

3. Method

This study used a cross-sectional design. Data from members of different interdisciplinary innovation teams was collected to elicit and analyze their respective TMM while they worked together on innovation projects. Experts evaluated each team's innovation performance during their final project presentation via a standardized assessment form. The degree to which the similarity of a team's TMM predicted the measured performance was used to evaluate the research hypothesis.

3.1 Sampling and procedures

A sample of interdisciplinary innovation teams was recruited from different education programs from the three largest universities in Munich, the Ludwig-Maximilians University of Munich (LMU), the Technical University of Munich (TUM), and the Munich University of Applied Sciences (MUAS), using a convenience sampling strategy. All three universities offer programs in which graduate student teams work on real-life product development or product design challenges for paying industry clients or startups. In all programs, the student teams are supervised by program coaches and company representatives. The setting is similar to a paid, external consulting project. This setup allowed the researchers to partly generalize their findings beyond the university setting to real-life innovation challenges. All project teams were comprised of members with different study backgrounds, such as computer science, business, engineering and psychology. The team's size varied between four to six members. Team members were actively matched to create teams that encompassed at least three different disciplinary backgrounds. The final sample consisted of 55 participants representing 15 interdisciplinary innovation teams.

3.2 Measurement scales

In earlier research, measuring *similarity* in TMMs had proven elusive. TMMs depend on their context, so there is no single way to measure them. Many different measurement methods have been experimented with, mainly depending on the subject population of each study (Mohammed *et al.*, 2010).

Langan-Fox, Code, and Langfield-Smith (2000) provided a comprehensive overview of various TMM measurement techniques, including repertory grids, card sorting, multidimensional scaling, ordered trees, pathfinder (PF), verbal protocol analysis and distance-to-ratio formulas. Mohammed, Klimoski, and Rentsch (2000) conducted a thorough meta-study on measuring TMMs and ultimately focused on four primary methods: multidimensional scaling, pathfinder (PF) and interaction- and text-based cause maps. The two articles agree that organized knowledge is central to TMMs, necessitating the

measurement of both content and structure. Content refers to the knowledge comprising cognition, while structure pertains to the organization of concepts in team members' minds. Elicitation techniques derive content, and representation techniques reveal structural patterns.

3.2.1 *Identification of relevant benchmarks for TMM measurement.* Research on TMMs began around 1990 and started to be published in peer-reviewed journals about ten years later (Mathieu *et al.*, 2000). To determine which elicitation and representation technique to use, the authors conducted a multi-step process to build a reliable research instrument. First, the existing meta-studies were collected and reviewed. Examination of the published meta-studies on TMMs from the year 2000 onwards yielded three studies: Mohammed *et al.* (2000, 2010) and DeChurch and Mesmer-Magnus (2010), analyzing a total of 63 previous research publications.

Mohammed *et al.* (2000) reviewed 23 studies and found similarity ratings (SR) to be the most popular method, with PF being a common structural representation. DeChurch and Mesmer-Magnus (2010) also analyzed 23 studies, differentiating between TMMs' relationship with team process and performance. They found SRs, particularly combined with PF, to show the strongest relation with team process, while cognitive mapping/content analysis showed the strongest relation with team performance. Despite not having the highest effect on performance, SRs and PF still demonstrated significant effects, making them the most effective and widely used techniques between the two meta-studies. A total of 14 of the studies included in the meta-analyses employed SRs and PF. Three of those were published with validated scales and sets: Lim and Klein (2006), Mathieu *et al.* (2000, 2005).

Following Mohammed *et al.* (2000), SRs were obtained by presenting participants with a set of statements (or items), asking them to consider each pair and rate their perceptions of the relation between the two (e.g. strongly agree or disagree that “*team members trust each other*” and “*the team is highly effective*” are related). PF, as described by Lim and Klein (2006), was used to generate a network structure from the raw scores (in this case, the scores of the SRs), capturing essential links and reducing noise. The similarity score between networks was calculated based on common links, ensuring an accurate assessment of TMMs. SRs were comprised of a set of items which needs to be validated as a whole.

3.2.2 *Categorization of items.* Next, the authors categorized these item sets. Four categories were identified: Coordination, communication, cooperation and background knowledge of team members. They map as follows (compare Chapter 2.1): *Team* (background knowledge) and *team interaction* (coordination, communication and cooperation). Both papers by Mathieu *et al.* (2000, 2005) do not include items on background knowledge, therefore lacking measurement of the team category and leaving Lim and Klein (2006) as the best fit for a validated item set. It consists of one, three, four and five items dedicated to communication, coordination, collaboration and background knowledge, respectively.

To adjust the imbalance, two additional communication items from Mathieu *et al.* (2000) were included. Examples of items and mappings include “*team members work well together*” (coordination), “*team members trust each other*” (collaboration), “*team members are similar to each other*” (background knowledge), and “*team members communicate openly with each other*” (communication).

To facilitate eliciting SRs for the TMM category of *team* and *team interaction* based on the set of Lim and Klein (2006), the authors custom-built a web-based tool that stores the subject's response and visualizes it through PF.

3.3 *Team performance assessment*

This study employed expert ratings via a custom assessment form to rate each team's performance, including the original assessment questions by Lim and Klein (2006). Lim and Klein studied unidisciplinary military teams, making it necessary to assess the need for any control variables before applying their performance measures to interdisciplinary, creative teams one-to-one. Their teams were all the same size and from the same military unit. The

sample in this paper includes graduate students from different courses with different team sizes. Even though the courses were similar in content, setup, and goal, there might be an in-between variance of performance attributed to e.g. different teachers, coaches or student selection, and some researchers suggest that there might be an “optimal” team size. To increase the robustness of the data set and the resulting conclusions, the authors controlled for the course and team size.

The subjects of [Lim and Klein \(2006\)](#) completed tasks such as securing a key installation and measuring directly translatable outcomes, whereas the teams in this paper presented their findings. The results were judged on creativity and innovation, which is less clearly measurable than a completed or failed task. To assess the “raw” team performance and not presentation skills, a third control variable called *selling and team* was included, as suggested by [Huber \(2017\)](#), together with the inclusion of measures mapped to the context of interdisciplinary teams tasked with creating innovation. All innovation teams, and the programs they were recruited from, had an emphasis on design thinking, which is a major influence on current new product development approaches ([Dym, Agogino, Eris, Frey, & Leifer, 2005](#)). Several authors, such as [Brown \(2009\)](#) and [Kelley and Kelley \(2013\)](#) have argued that innovation teams need to discover what would be a desirable solution from a customer’s point of view. The teams should also propose technologically feasible solutions. Besides, innovation teams must implement and scale the potential solution via a viable business model. Therefore, *desirability*, *feasibility* and *viability* were included as assessment criteria in evaluating each innovation team’s performance. Lastly, an additional item called “*investment intent*” as suggested by [Kornish and Ulrich \(2014\)](#) was added to assess the potential of a “raw idea”.

3.4 Measurement process

All participants received a short briefing about the purpose of the study and the functionality of the web-based tool. Participants rated the relatedness of all pairs of items (136 pairs from 16 items) on a nine-point Likert scale (1 = “highly negatively related” to 9 = “highly positively related”). After the participants had filled out the survey, a log file with the raw data was created and used as input for the structural assessment technique in PF. It visualizes the data as network graphs and produces a spatial representation of the relationship between items, where items are represented as nodes and the relationship between items is depicted as links between nodes. The single-source Dijkstra algorithm ([Dijkstra, 2022](#)) was used to generate each team member’s graph as a representation of their mental model.

3.4.1 TMM similarity. Similarly to [Lim and Klein \(2006\)](#), this study utilized averaged deviations as the measurement for TMM similarity. Other studies in the past have followed the same strategy, e.g. [Marks et al. \(2000\)](#) or [Stout, Cannon-Bowers, Salas, and Milanovich \(1999\)](#). The specific steps are: (1) use PF to assess the similarity between each dyad of the individual team member’s mental models and (2) average the similarity scores for all dyads within the team to calculate the average similarity of team members’ TMMs. The similarity score can range from 0 to 1. For example, a 0.6 similarity score means that 60% of the mental model structure is shared.

3.4.2 Team performance. All of the selected education programs contained a final presentation at the end, where each team presented its work. These presentations were utilized to assess the teams’ performances. Each presentation was rated by several experts, who were chosen based on research findings by [Amabile \(1982\)](#), regarding the theory of the consensual assessment technique, which is described as the “gold standard” ([Cseh & Jeffries, 2019](#), p. 2) of creativity assessment for research purposes ([Cseh & Jeffries, 2019](#); [Kaufman, Lee, Baer, & Lee, 2007, 2008](#)). Amabile argues that the only relevant requirement for someone assessing the value of performance is familiarity with the domain of endeavor in which the product was made. Therefore, the experts rating the team performances were the instructors and coaches of the teams in each course format.

3.5 Analysis

The data analysis follows a generalization approach, where the authors extract qualitative data and analyze it through quantitative methods. In principle, the collected data can be evaluated in different ways: the weights of the links can be incorporated into the similarity rating or not, and either the individual or averaged deviation from the average TMM can be measured. This means a total of six different ways to interpret the data.

H_0 was tested by regressing the team performance ratings provided by the expert assessments on the TMM similarity that was provided through the SRs and PF after controlling for *course*, *team size* and *selling and team*. The control variables and their coefficients were incorporated in the data analysis to verify the need to control for them.

Performance is a meta-variable, measured through a combination of six items: *efficiency*, *quality*, *desirability*, *viability*, *feasibility* and *investment intent*. Each of those variables was also regressed individually on TMM similarity, to understand if there is a difference in their predictive power.

4. Findings

The following research findings show a significant positive correlation between TMM similarity and innovation team performance. In the following discussion, the authors also revisit the findings of [Lim and Klein \(2006\)](#).

[Table 1](#) shows the minimum, maximum, mean and standard deviation for the TMM similarity, as well as for the performance measure. The authors used hierarchical regressions to account for control variables. As depicted, TMM similarity is significantly positively related to performance. As shown in [Table 2](#), TMM similarity accounts for 42.1% of the variance in team performance ($F(4,50) = 12.75, p < 0.01$). TMM similarity as a predictor was significant ($p < 0.01$). The results support H_a and show that a high similarity in TMMs is positively connected to innovation performance ratings.

In contrast to this study, [Lim and Klein \(2006\)](#) only based team performance on the average of the two variables: *efficiency* and *quality*. As their study forms the initial baseline for this research, the authors wanted to explicitly discuss how the newer findings relate to Lim and Klein's previous conclusions. Step 1 was to confirm that the correlation between *efficiency* and *quality* is significant, which it is ($r = 0.40, p < 0.01$). Step 2 was to regress team performance on TMM similarity after controlling for the *course*, as Lim and Klein controlled for the equivalent combat unit. This paper's analysis rejects the previous claim that TMM similarity influences team performance when measured as the average of *efficiency* and *quality*, controlled for the *course*. As Lim and Klein's study was set in a different context (Singaporean military training teams of the same size), there was no need to control for either *team size* or *selling and team*, in contrast to this study. When incorporating those two control variables, the regression proves to be significant ($F(4,50) = 5.733, p < 0.01$), with the coefficient also being significant ($p < 0.05$). This confirms that Lim and Klein's study can be replicated, obtaining the same results, even if the setting and sample are different.

Table 1. Descriptive statistics

Measurements	<i>N</i>	Minimum	Maximum	Mean	SD	R^2_1	R^2_2
Avg. SS	55	0.35	0.88	0.5389	0.13691	–	–
Avg. Int. Performance	55	3.89	8.00	5.4458	1.04283	0.073*	–
Avg. Performance	55	5.42	7.83	6.8691	0.70025	0.465**	0.001

Note(s): * $p < 0.05$; ** $p < 0.01$

Source(s): Authors' own work

Table 2. Hierarchical regression of team performance on TMM similarity

Measurements	B	SE B	β	R^2
<i>Step 1</i>				
Course	-0.361	0.129	-0.475**	
Team Size	0.145	0.105	0.245	
Selling and Team	0.523	0.092	0.733**	
<i>Step 2</i>				
Avg. Performance	2.192	0.718	0.428**	0.421**

Note(s): * $p < 0.05$; ** $p < 0.01$
Source(s): Authors' own work

Performance was treated as a meta-variable, measured through a combination of six items (compare Chapter 3.5). When regressing each of those variables individually on TMM similarity, the results suggest that TMM similarity predicts most strongly for the combined variable of *efficiency* and *quality*, then *efficiency* alone ($F(4,50) = 6.609, p < 0.01$; coefficient: $p < 0.01, R^2 = 0.346$), the combined variable of *desirability, viability* and *feasibility* ($F(4,50) = 8.713, p < 0.01$, coefficient: $p < 0.01, R^2 = 0.411$) and *viability* ($F(4,50) = 10.742, p < 0.01$, coefficient: $p < 0.01, R^2 = 0.462$) and *feasibility* ($F(4,50) = 16.767, p < 0.01$, coefficient: $p < 0.01, R^2 = 0.573$) alone.

When looking at the coefficients of the control variables *course, team size* and *selling and team* in Table 2, *course* and *selling and team* are significant alongside average performance. This means that those are indeed factors worth controlling for, factors that would have influenced the regression otherwise and therefore distorted the outcomes.

Looking at regressing the six items making up performance individually on TMM similarity, TMM similarity always correlates with *viability* and *feasibility*, in addition to *efficiency*. The paper also looked at the exploration of nonlinear coherences. To analyze the data further, the authors also explored fitting the data to non-linear models in addition to linear models: A curve-fitting regression by the individual performance variables on TMM similarity showed a significant U-shaped coherence between TMM similarity and *desirability* ($R^2 = 0.390, p < 0.01$) and *selling and team* ($R^2 = 0.371, p < 0.01$). However, TMM similarity and *efficiency* proved to be a very linear coherence ($R^2 = 0.166, p < 0.01$), even when the authors tried to perform a curve-fitting regression.

It is essential to analyze an assessment form's internal consistency and reliability, especially when measuring noncategorical data (Taber, 2018). The Cronbach's alpha reliability score was 0.805, which is an acceptable threshold.

5. Discussion

5.1 Discussion of findings

The results suggest that a high TMM similarity is connected to better team performance in interdisciplinary innovation teams. This validates the assumptions of Badke-Schaub *et al.* (2007) and echoes the findings of other studies that observed similar effects in unidisciplinary teams (e.g. Mathieu *et al.*, 2005; Marks *et al.*, 2000). The findings reiterate that “speaking the same language” is essential in teamwork. They also contribute to the discussion of what influences the performance of innovation teams, with a specific focus on interdisciplinary innovation teams that work on open-ended creative tasks.

In analyzing the factors contributing to the meta-variable of performance, it is evident that *efficiency, viability* and *feasibility* consistently show positive correlations across various courses and team sizes. Conversely, *selling and team* is negatively related to TMM similarity and must be controlled for when evaluating raw team performance. Notably, *desirability* and

quality also exhibit negative correlations with TMM similarity when *selling and team* is not controlled.

Teams with high TMM similarity tend to be efficient and realistic, making reasonable project assumptions and being trusted to complete tasks. However, these teams may lack the charisma to create highly innovative and desirable products. This observation could reflect assessor biases, where realistic and efficient teams are favored over innovative but less cohesive ones.

Non-linear relationships reveal that *desirability* and *selling and team* have a U-shaped relation to TMM similarity, with a minimum at approximately 60% similarity. This suggests that teams with either very high or very low similarity are more likely to produce desirable products and present them effectively. Average similarity teams may lack both the innovative tension of dissimilar teams and the smooth harmony of highly similar teams, making them harder for assessors to evaluate.

These findings highlight the need for further research to understand the underlying reasons behind these correlations and their implications for team performance assessment. This paper found that the authors were successful in replicating the study of [Lim and Klein \(2006\)](#) and obtaining the same results, even if the setting and sample were different, suggesting that a similar study design can be used to drive further research.

While this paper provides further evidence that a shared mental model is essential in teams, it did not address the many other aspects of team performance, such as resilience and the capacity to bounce back from setbacks ([Kirkman & Stoverink, 2021](#)). Fostering a shared mental model in a team also becomes more difficult in virtual teams ([Morisson-Smith & Ruiz, 2020](#)) that heavily rely on digital technologies – yet this is the setting for many knowledge worker teams after the COVID pandemic has been curtailed. In such environments, developing a shared mental model about the use of technology offers a preventive strategy for negative effects such as increased psychological strain due to uncoordinated use of digital communication technologies, also referred to as techno-frustration ([Müller et al., 2023](#)).

5.2 Limitations

To increase internal reliability, the authors built upon validated items and scales from other studies and elicited TMMs by letting participants rate the relationship of items to each other. A larger sample size could have increased its statistical power, even though the final sample of 15 interdisciplinary innovation teams was comprised of a total 55 study participants which is an acceptable study sample size ([Riemer & Schrader, 2016](#); [Vinokur-Kaplan, 1995](#)) and holds a statistical power of 0.86. The data was gathered through convenience sampling in a specific setting, with the study participants being graduate students in courses for creative, innovative, time-restricted product development for open-ended innovation challenges. While this mimics how innovative teams work in real-world corporate and agency settings, the study's generalizability could have been improved by focusing on study participants directly embedded in organizations (see Chapter 3.1). Also, to ensure full generalizability of the results, the study should be repeated with random sampling, taking particular care when evaluating qualitative data with quantitative methods (see Chapter 3.5). Furthermore, this work evaluates specific TMMs (the *similarity of team and teamwork*, deemed most relevant to exploring the research hypothesis, see Chapter 2.3) while excluding others. Lastly, team performance was assessed via expert ratings. Even though this follows the work of [Amabile \(1982\)](#) and the example of [Lim and Klein \(2006\)](#), it is still a subjective rating.

6. Conclusion

This study expands on prior research by exploring the role of TMMs in interdisciplinary innovation teams, an area that has received less attention compared to unidisciplinary contexts. Building on the foundational work of [Lim and Klein \(2006\)](#) and validating the assumptions of

other researchers such as Badke-Schaub and Frankenberger (2004), Badke-Schaub *et al.* (2007), Casakin and Badke-Schaub (2015) and Neumann *et al.* (2006), it examined how TMM similarity influences team performance in complex, open-ended tasks.

The findings indicate a link between high TMM similarity and improved performance in interdisciplinary innovation teams, contributing to existing theoretical frameworks and the broader discussion on teamwork and innovation and deepening our understanding of TMM similarity in interdisciplinary contexts.

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