

TEAM DYNAMICS & AI MEDIATION: THE CENTRALITY OF DECISION-MAKING IN DESIGN ENGINEERING HIGHER EDUCATION

Katherine LUO and Stephen GREEN
Imperial College London, United Kingdom

ABSTRACT

Multidisciplinary collaboration is central to engineering and product design education, where project-based learning requires students to integrate diverse expertise and perspectives. However, early-stage team decision-making is often informal and weakly structured, leading to fragmented knowledge sharing, limited traceability, and uneven participation. From an EDI perspective, such fragmentation can disproportionately affect whose knowledge is surfaced and recognised. This study investigates how an AI boundary tool can support decision-making without undermining student agency. Grounded in a KS–DM Boundary Model derived from initial empirical work, an AI Figma plugin was developed to scaffold discussion rather than generate solutions. Findings indicate improved decision traceability, temporal structuring, and internal alignment, while adoption depended on summary quality and contextual accuracy. The study demonstrates that constrained, process-level AI can support inclusive collaborative learning in DE-HE while preserving student authorship and creative responsibility.

Keywords: Design engineering, decision making, boundary objects, AI, teamworking

1 INTRODUCTION

Multidisciplinary teamworking is increasingly central to professional practice and higher education, particularly in design engineering (DE) where project-based learning (PBL) dominates [1]. In such settings, early-stage decision-making (DM) often have long-term consequences in shaping project direction, scope, and prioritisation [2]. However, student teams typically lack structured leadership and procedural guidance, and decision processes tend to remain implicit and embedded within ongoing discussion. Consequently, DM depends heavily on how effectively team members share, interpret, and integrate knowledge—a dynamic process referred to as knowledge sharing (KS) [3]. When KS is fragmented or uneven, teams experience looping discussions, loss of focus, unequal participation, and weak decision traceability. Collectively, these issues reduce decision efficiency and hinder the development of shared understanding during a critical phase of collaboration. Existing models of DM and KS provide valuable theoretical foundations, but many originate from domains such as healthcare or business, where roles, authority, and decision criteria are relatively stable [4]. In contrast, student PBL teams operate in dynamic, exploratory environments where decision points emerge fluidly and knowledge is exchanged in real time through conversation and evolving artefacts. Initial empirical work in design engineering (DE) education has shown that conventional models often fail to capture how knowledge is externalised, internalised, and integrated during live team discussions. This gap highlights the need for context-sensitive approaches that reflect early-stage student collaboration challenges and support actionable interventions. The concept of boundary objects (BOs)—artifacts used to share, exchange, integrate and create new knowledge [5]—offer one route to supporting KS in multidisciplinary collaboration. In design engineering higher education (DE-HE) contexts, BOs may function as platforms, facilitators, or mediators, and take multiple forms, including physical artefacts (e.g., prototypes, Post-it notes), visual or verbal tools (e.g., whiteboards, digital canvases), and conceptual models (e.g., frameworks, process maps). While these artefacts support externalisation, they are often static, inconsistently maintained, or poorly integrated into fast-moving discussion. Consequently, decision rationale may remain tacit, be lost during topic shifts, or be unevenly accessible across team members. Integrating Artificial Intelligence (AI) into higher education presents both significant opportunities and ethical challenges. To date, AI adoption in higher education has largely

focused on system-level optimisation, such as automated feedback or tutoring tools [6]. However, by positioning AI as a powerful problem-solving agent, such approaches risk expanding its functional scope to the extent that students may become reliant on AI-generated solutions, raising concerns regarding agency, skill development, and over-dependence. In contrast, comparatively little attention has been paid to AI's role in supporting students' real-time collaborative learning processes. Existing AI meeting tools typically generate transcripts or summaries but are rarely embedded within design workflows or structured to scaffold decision-making. To address this gap, the study developed a workflow-integrated AI boundary tool implemented as a Figma plugin. Figma was selected as it is already widely used by DE students as a shared workspace [7]. Embedding the intervention within this platform minimised disruption and onboarding friction. The plugin augments rather than replaces existing boundary artefacts and is grounded in the KS-DM Boundary Model (see Figure 1), synthesised from prior empirical observation of multidisciplinary DE student teams. The model conceptualises DM as a recursive, knowledge-driven process involving externalisation, internalisation, and integration. Observations revealed that the KS and DM process was not consistently completed, with some stages missing or underdeveloped. Recurring barriers were also identified across KS and DM. The plugin was designed to address these identified barriers. Its role was intentionally limited to supporting the process itself—structuring discussion, making reasoning visible, and highlighting overlooked contributions—without generating solutions or replacing team decision-making. By embedding this controlled form of AI support within authentic PBL activities, the study evaluates how targeted process intervention can influence collaborative decision-making in design education. Accordingly, this study addresses the following research questions: (RQ1) How do KS and DM process barriers manifest in live, time-limited multidisciplinary student team discussions, and to what extent can the AI-integrated Figma plugin mitigate them? (RQ2) To what extent does a workflow-integrated, deliberately constrained intervention improve short-term DM efficiency, shared understanding, participation inclusivity, and perceived team performance? (RQ3) What workflow frictions, breakdowns, and adoption challenges emerge when embedding the intervention within the existing workspace? (RQ4) How can issues of student agency and academic integrity be addressed when deploying such AI support in design engineering education?

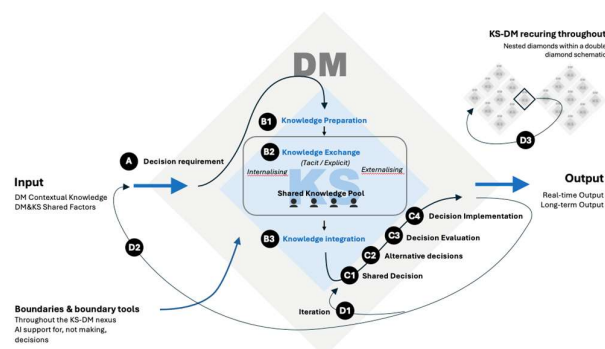


Figure 1. KS-DM (Knowledge Sharing – Decision Making) Boundary Model

2 METHODOLOGIES

This study adopts an intervention-oriented mixed-methods approach, building on initial empirical research that developed the KS-DM Boundary Model and identified key process barriers. The model was derived from a four-week naturalistic observation study of DE student team meetings, in which recurring KS and DM process barriers were identified through thematic coding. The present study focuses on operationalising these findings through the development and evaluation of a functional prototype. The methodology comprises three stages: (1) prototype development, (2) workshop-based deployment, and (3) qualitative evaluation of decision-making processes.

2.1 Prototyping Methodology and System Development

The Figma plugin was developed as a high-fidelity, fully deployable prototype designed for stable use in live collaborative workshops. It can be easily installed and operated within the Figma ecosystem, with emphasis placed on robustness, cross-session reliability, and minimal runtime disruption. Methodologically, the system adopts a modular architecture separating recording, processing, storage, and visual rendering. Due to Figma's limitations on persistent audio access and background processing,

recording and AI analysis are handled externally via a browser interface hosted on Vercel. Serverless API routes manage transcription and analysis, Supabase provides structured storage and session traceability, and the plugin functions as the visual interface layer within the workspace. Speech recognition and speaker segmentation are handled through AssemblyAI, preserving conversational structure and ensuring that multi-participant dialogue can be reconstructed accurately. Speech recognition and speaker segmentation are performed using AssemblyAI to preserve conversational structure. A two-stage processing pipeline supports both incremental, near real-time updates during sessions and a consolidated full-session synthesis after the meeting. Analytical requests are governed by a configurable prompt-generation library, which dynamically adapts prompts based on contextual parameters while maintaining consistent output structure. AI responses are constrained to predefined formats to ensure reliable rendering. Overall, the system prioritises operational stability, modular separation of functions, and seamless integration into existing collaborative workflows.

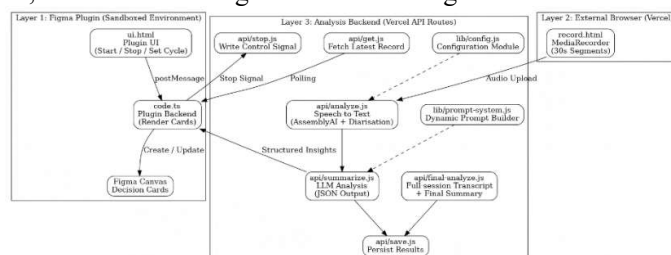


Figure 2. Plugin Product Architecture

2.2 Workshop based deployment

Following iterative prototype refinement and pilot use in tutor–student meetings, the intervention was evaluated through four structured workshops with pre-existing multidisciplinary student teams. Sixteen participants took part (four teams of four). An A/B design was adopted: two teams (Condition A) completed the task without the plugin, while two teams (Condition B) used the plugin. Each one-hour workshop involved an early-stage conceptual design task based on a breadmaker brief. Teams were required to (1) define a primary user, (2) identify three key pain points, and (3) propose a final concept, with decision points structured at 10-minute intervals to ensure observable DM stages within the session. The brief was intentionally designed to be accessible yet unfamiliar to participants. The brief was intentionally designed to be accessible yet unfamiliar to participants, reducing prior knowledge bias and enabling comparable starting conditions. The format allowed controlled comparison across defined decision stages, while focusing on short-term process effects rather than long-term behavioural change.

2.3 Qualitative evaluation of the decision-making processes

All workshops were recorded and transcribed alongside facilitator observation notes for analysis independent of the plugin interface. Manual semantic coding was conducted to record KS barriers, DM stage transitions, and behavioural patterns. Coding captured occurrences of KS barriers, DM–KS loop cycles, time intervals between decision stages, and interaction changes following AI-generated decision cards. Coding categories were predefined based on the KS–DM boundary model to maintain analytical consistency. Post-workshop surveys were collected individually using five-point Likert scales across dimensions including perceived decision efficiency, clarity of reasoning traceability, understanding of selection logic, and individual contribution for the three key decisions, with team-level means used for cross-condition comparison. In the plugin condition, AI-generated summaries served as an additional artefact for analysing decision traceability and interaction dynamics. The evaluation therefore focuses on immediate process-level impacts within the workshop setting.

3 RESULTS

Results are reported in relation to the studies research questions RQ1-3. Issues of student agency and academic integrity (RQ4) are explored in the discussion section.

3.1 The Final Prototype

The plugin operates through four structured steps. First, users configure the meeting by selecting the meeting type, module, roles, team details, and goals, and may upload project PDFs or previous

summaries to ensure continuity and link the session to the appropriate analytical prompt. Second, they set the summary interval, determining how frequently Decision Cards are generated based on meeting length and team preference. Third, during the session, the plugin processes discussion in the background and generates structured Decision Cards on a dedicated Figma canvas, separating explicit knowledge (stated decisions and reasoning) from tacit knowledge (implicit assumptions). Fourth, at the end of the meeting, it produces a Final Meeting Summary that consolidates decisions, synthesised knowledge, and progress indicators, supporting goal alignment, gap identification, and decision traceability across stages.

3.2 Manifestation of KS–DM Process Barriers and AI Mitigation

Table 1 summarises the comparative manifestation of KS–DM barriers across conditions. In the non-plugin condition, several barriers were evident. Key decisions were rarely documented during discussion, resulting in weak traceability and incomplete consolidation of reasoning. Topic switching frequently disrupted decision stages, and tacit insights, although expressed, were not systematically integrated into shared understanding. In the plugin condition, these barriers were mitigated through three primary mechanisms. First, the tool functioned as a shared knowledge pool, capturing discussion content and maintaining visible records of decisions within the workspace. Second, periodic decision cards introduced structured checkpoints that reduced topic drift and reinforced stage progression. Third, the explicit–tacit structure clarified reasoning and supported more consistent knowledge externalisation. Rather than replacing DM, the AI-supported boundary tool stabilised discussion cycles by consolidating and visualising collective insights, thereby improving continuity and reducing fragmentation.

Table 1. Indicative Occurrence of KS–DM Barriers Across Conditions

KS–DM Barriers	Non-Plugin participants	Plugin participants
Forgetting Key Discussion Points	Key decisions were rarely documented during discussion; summarisation often incomplete, leading to overlooked points.	Periodic decision cards record key decisions and supporting rationale, enabling teams to revisit and verify prior reasoning.
Loss of focus due to frequent topic switching	Frequent topic drift within stages; discussion often re-centred only after facilitator prompts.	Topic drift occasionally observed, but periodic card generation re-anchors discussion to prior decisions.
Blurred distinction between explicit & tacit knowledge	Tacit insights articulated but not systematically integrated into shared reasoning.	Explicit–tacit distinctions surfaced within structured summaries, improving knowledge visibility.
Collaboration Tools & Styles Misalignment	Minor coordination inconsistencies within shared workspace.	Minor misalignment observed; shared summaries enhanced alignment across members.

3.3 Impact on Short-term DM Efficiency, Shared Understanding, and Participation

Building on the KS–DM barrier analysis in Section 3.2, impacts were examined across DM efficiency, shared understanding, and participation. Overall survey rating differences were moderate, but clearer effects emerged in temporal regulation and decision traceability. **DM efficiency** was reflected in perceived time allocation and confidence in implementation. In the plugin condition, participants reported clearer stage boundaries and reduced need to revisit unresolved points. Transcript analysis showed fewer DM–KS loops and reduced topic drift following periodic decision cards. During final presentations, plugin teams demonstrated stronger recall of selection logic, indicating improved traceability and greater confidence in the feasibility of their decisions. The intervention did not accelerate discussion speed but supported more deliberate progression across stages. **Shared understanding** was assessed through variance in team members’ ratings and consistency in decision explanations. In the plugin condition, smaller gaps were observed across alignment-related survey items, indicating stronger internal agreement. During presentations, plugin teams provided more consistent justifications for decisions, suggesting more stable consolidation of reasoning. **Participation** was evaluated through speaking distribution (transcript analysis) and self-reported contribution. Structured review moments around decision cards led to more balanced articulation during key checkpoints. Participants also reported greater awareness of their own and others’ contributions. These effects appeared to arise partly from an indirect mechanism: the presence of the AI system introduced a reflective monitoring dynamic. Knowing that discussions would be captured and reflected back in real

time increased attentiveness to articulation, encouraging clearer expression and more deliberate engagement. The returned summaries also functioned as confirmation mechanisms, reinforcing alignment and strengthening confidence in decisions. Together, these effects indirectly supported perceived efficiency and collaborative participation.

3.4 Frictions and Adoption Challenges with AI Boundary Tool integration

While short-term integration was technically smooth, several frictions and adoption challenges emerged. A key short-term friction concerned the contextual accuracy and perceived value of the Decision Cards. Adoption was highly dependent on the quality of the summaries: when cards were perceived as precise and contextually aligned, engagement remained strong; however, when later cards contained repetitive or overly general content, participants reported reduced trust and diminished willingness to use the tool. This suggests that perceived accuracy and relevance are critical determinants of sustained use. Participants also requested stronger traceability features, such as quotations or timestamps linking to the explicit, tacit statements. These concerns highlight a limitation of current AI processing: output clarity and reliability depend heavily on prompt design and contextual framing. Although the prompt-generation system adapts to meeting inputs, users indicated that more precise prompting, more advanced model and stronger contextual linking would improve consistency across sessions. Long-term adoption challenges were also evident. Unlike AI tools that provide direct solutions or immediate performance gains, this intervention focuses on structuring discussion rather than generating ideas. During the final concept stage, one team asked, “AI, please brainstorm for me,” revealing a tension between the tool’s process-support role and expectations of AI as a solution generator. This highlights the need to clearly define the boundaries of AI assistance in design education. Overall, adoption depends on summary quality, contextual accuracy, and clear expectation setting. Sustained engagement requires improved precision, stronger traceability, and clearer boundaries for AI’s role in collaborative creativity.

4 DISCUSSIONS

The KS–DM boundary model (Figure 1) provides a framework for examining student agency and academic integrity in AI-supported DE education. By clarifying the role of DM within the design process, the model helps define operational boundaries for responsible AI integration in DE pedagogy. The following discussion interprets the findings in relation to RQ4:

- A. In DE-HE, **decision requirements** are often shaped by project briefs and tutor guidance. Determining what decisions need to be made is itself a learning outcome and should not be delegated to AI. While participants requested stronger scaffolding, the plugin did not decide for the team. Users defined meeting details in the configuration step, and the AI adapted its prompts accordingly. This demonstrates that students set the direction, while the AI responds to their defined needs to enhance clarity and generate more relevant outcomes without replacing student judgement.
- B. In a team context KS stages include; **B1. Preparation** – Teams are not always effective at independently gathering relevant knowledge. AI can make this process more efficient by suggesting multiple sources, but students must define what to search and critically select evidence themselves. They should not rely solely on AI-generated answers, especially when primary data—such as user surveys or real user insights—is required. AI may recommend sources, but responsibility for framing questions and validating evidence must remain with students. **B2. Exchange** – When knowledge primarily resides with an individual, it has limited value to the team. Students are often not adept at exchanging knowledge effectively, making boundary tools such as sketches or shared boards vital. Frictionless input and output from multiple tools cannot currently be achieved with AI platforms which tend to focus on one communication medium. As this stage frequently involves brainstorming, AI intervention must be carefully constrained. Direct solution generation risks narrowing the solution space and limiting creative exploration. Instead, AI should support visibility, organisation, and reflection without replacing the team’s ideation process. **B3. Integration**, or a shared mental model, of critical knowledge is difficult to achieve and to verify. AI as a boundary tool can play a significant role in streamlining collation and reporting on knowledge integration in real-time. A recurring usability requirement from the workshop was traceability: participants requested that explicit/tacit statements be supported by short quotations or timestamps from the conversation, as the lack of provenance reduced interpretability and trust.

- C. **C1. Shared Decision:** AI can document shared decisions and support evaluation, but it should not make decisions for the team. **C2. Alternative Decisions:** While AI may assist divergent exploration, students remain responsible for generating and critically assessing alternatives. **C3. Decision Evaluation:** AI and other team outputs must be subject to explicit critical review rather than implicit acceptance, as is often the case in existing DE-HE practice. Developing students' capacity for critical evaluation is therefore essential. AI-generated outputs should also be transparent in their reasoning, with students understanding how and on what basis results are produced. Making the underlying logic visible helps prevent blind trust, over-reliance, and uncritical acceptance of AI suggestions. **C4. Decision Implementation:** With previous steps shared and verified through AI, DM implementation is supported with a robust evidence trial.
- D. Highlighting **iteration** as a key characteristic of DE, shown on the model as looping process, reflects the reality that iteration happens throughout DM sub-process (D1), the overall KS-DM process (D2), and within the overall DE process (D3).

5 CONCLUSIONS

AI integration in design engineering higher education need not solely centre on solution generation or efficiency gains. Instead, evidence from our evaluation suggests that carefully constrained, workflow-integrated AI can stabilise collaborative decision-making processes by improving reasoning visibility, temporal regulation, and decision traceability. These effects were most evident in reduced fragmentation across KS-DM cycles and stronger internal alignment during final articulation of decisions. From a design education perspective, the key contribution lies in reframing AI as a boundary tool that mediates team dynamics rather than replacing cognitive effort. By making tacit and explicit reasoning visible, the intervention supports more inclusive participation in multidisciplinary teams, particularly where diverse expertise may otherwise remain under-recognised. Importantly, the development of a fully functional, deployable Figma plugin provides a practical foundation for ongoing experimentation in authentic educational settings. It enables testing across multiple year groups, team configurations, and tutor-student contexts, offering a scalable platform for future research. Findings reinforce that AI should scaffold collaborative cognition while preserving student authorship, judgement, and critical evaluation practices. However, the study is limited by its small sample size (N=16), short-term workshop format, and reliance on perceptual measures. Longitudinal impacts on learning development, academic integrity behaviours, and sustained adoption cannot be inferred. Future research should examine extended deployment across multiple cohorts and contexts, refine traceability mechanisms, and develop robust pedagogical metrics for evaluating AI's influence on collaborative learning rather than productivity alone. Responsible AI integration in design education must therefore prioritise mediation of team processes over delegation of decision authority, ensuring that diversity of thought is surfaced, examined, and critically negotiated within evolving collaborative environments.

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