# The Planning and Implementation of AI-Generated Rich Tasks in Primary Mathematics Classrooms

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This paper examines how three Australian primary teachers used generative AI to design and implement rich mathematical tasks. Drawing on multiple data sources analysed using three theoretical lenses, findings indicate that while generative AI expanded planning possibilities, the richness of tasks depended on teacher enactment rather than AI output. Teachers with deeper mathematical knowledge for teaching crafted more intentional prompts, critically evaluated outputs, and adapted tasks responsively, positioning professional knowledge as decisive in whether AI-supported task design enhances or constrains meaningful mathematical learning.

The emergence of publicly available generative AI (GenAI) in late 2022 has significant implications for mathematics education. Evidence suggests that AI holds considerable potential to support and enhance teaching practice across educational contexts (Wayne et al., 2023). Digital resources have long been recognised for their capacity to disrupt traditional pedagogical approaches (Attard & Holmes, 2020), and, in the case of GenAI, may also contribute to alleviating high teacher workloads (Granziera et al., 2025). However, research consistently demonstrates a lag between the emergence of new technologies and scholarly examination of their implications for teaching and learning (Granić, 2022).

Although research on the use of GenAI tools in education continues to emerge, there are clear gaps. For example, literature that specifically refers to mathematics education tends to focus on high school or tertiary levels (Egara & Mosimege, 2024). There is a gap in empirically informed literature that addresses the impacts of primary teachers' use of GenAI tools to develop quality tasks and resources for mathematics education.

This paper presents findings from a study conducted in Australian primary mathematics classrooms examining the potential value and impact of GenAI as a tool to create rich mathematical tasks for primary classrooms. The paper presents findings pertaining to three teachers' experiences planning and implementing AI-generated tasks.

## Background

Teacher adoption of GenAI for instructional purposes is accelerating, though uptake remains uneven. US data indicates that teachers of mathematics report lower use for planning or instruction, and teachers in low-socioeconomic schools report lower adoption rates (Kaufman et al., 2025). Australian large-scale data are limited, though early evidence suggests weekly AI use for planning, assessment, and feedback (Blundell et al., 2025). Teachers under high stress and time pressure are more likely to value AI tools (Collie & Martin, 2024), yet efficiency-driven uptake may foster uncritical use of materials designed for hypothetical rather than specific classrooms.

Research on AI-generated mathematics content supports this concern. Teachers can perceive AI-generated lesson plans as generic and vague, lacking the specificity needed for immediate classroom use (Walkington, 2025). Similarly, Rutherford et al. (2025) found that teachers valued ChatGPT for generating ideas but were frustrated by limitations in producing cohesive resources; however, lessons developed with ChatGPT resulted in more motivationally supportive teacher language and reduced student boredom. Mathematics teachers describe AI

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lesson plan outputs as a useful starting point that requires iterative modification through prompting to meet classroom needs (Aga et al., 2024). However, the quality of this iteration can vary; Dilling and Herrmann (2024) found pre-service mathematics teachers' interactions with large language models (LLMs) were primarily superficial, with teachers using a limited range of prompts. Effective prompt crafting is itself an emerging professional skill grounded in teachers' pedagogical and content knowledge (Biton et al., 2025).

Despite these affordances, GenAI can produce mathematically inaccurate or developmentally inappropriate content (Sawyer & Aga, 2024). Pre-service teachers (PSTs) may struggle to detect such errors; Kim et al. (2026) reported 33.8% of errors in ChatGPT-generated fraction problems went undetected. Critically, PSTs with stronger Mathematical Knowledge for Teaching (MKT) were more critical of AI-generated plans (Aga et al., 2024), and more accurate in identifying pedagogical weaknesses (Gurl et al., 2025). These findings suggest the capacity to effectively negotiate AI outputs for mathematics lesson planning may depend on the depth of teachers' own mathematical and pedagogical knowledge.

The findings also have particular implications for the design and use of rich mathematical tasks. Rich mathematical tasks are broadly characterised by being authentic to real world applications, accessible but challenging for students at multiple levels, having multiple solution pathways, and provide opportunities for reasoning, mathematical connections, and discussion (Moulds, 2002). Critically, research consistently demonstrates that a task's richness is not an inherent property of the task itself but is realised through its enactment in the classroom (Piggott, 2011), and tasks frequently decline in cognitive demand during classroom implementation (Tekkumru-Kisa et al., 2020). This enactment-dependent nature is particularly significant in the context of AI-generated lesson plans, where the tool may produce something that structurally resembles a rich task but cannot ensure its mathematical potential is realised in practice.

The way that GenAI is perceived by teachers impacts their uses, and student learning outcomes of this use (Alwaqdani, 2025). Teachers play a central role in interpreting and integrating AI into mathematics learning, and this is particularly the case in the planning and implementation of rich mathematical tasks. This paper presents an investigation of how three primary teachers used GenAI to design rich mathematical tasks, and how their MKT shaped both the planning process and classroom enactment of those tasks.

## Methods and Methodology

This qualitative multiple case study aimed to develop a nuanced understanding of the implications of using GenAI to support the development of rich tasks for teachers of primary mathematics. The study was guided by the following research questions:

- In what ways do teachers use generative AI to produce primary mathematics rich tasks?
- What are the implications for the use of GenAI to design rich tasks for primary teachers?
- What are the implications of the use of AI-generated rich tasks for primary students?

Data informing this paper are drawn from a larger study comprising 34 case studies across nine schools (in NSW, WA, and the ACT), from a range of socioeconomic areas. Each case consisted of a teacher and their students. Teachers were recruited via professional networks, and data was collected from during 2025. Ethics approval was granted by the Western Sydney University Human Research Ethics Committee. Schools and participants were anonymised, and pseudonyms used throughout. Three cases were selected to represent the variation in the implementation of AI across different school contexts. Table 1 summarises the cases analysed and demographic information for the participants included in this paper.

**Table 1**

| | Case A | Case B | Case C |
|---|---|---|---|
| **Teacher Name** (Pseudonym) | Olivia | Audrey | Tania |
| School Demographic | Non-government, large school in high SES area | Government, medium school in mid SES area | Government, small school in mid SES area |
| Teacher Career Stage | Early | Mid | Late |
| Grade | 5 | 3/4 | 1 |
| Lesson Title | 'Can You Beat the Spinner?' | 'Decimal Dilemma at the Market' | 'Fraction Lines' |
| Task Topic | Chance and probability | Decimal place values | Linear fractions |
| Task Activity | Students designed and tested a spinner game in pairs, predicting fairness by recording outcomes across 20 spins. | Students created a shopping list, using place value and decimals to calculate totals and stay within a set budget | Students divided lolly snakes and Play-Doh into halves and quarters to explore linear fractions. |

Data collection consisted of pre- and post-interviews with teachers, one AI planning session, three classroom observations per teacher, student focus groups, and AI chat planning artefacts. Pre-interviews explored teachers' existing attitudes toward and experience with GenAI, while post-interviews captured reflections on the planning and implementation process. In the AI planning session facilitated by the research team, teachers interacted with a GenAI tool to design three rich mathematical tasks and accompanying lesson plans. Teachers in NSW government schools used NSWEduChat, their approved platform, while the other teachers selected their preferred tool (ChatGPT or Claude). During the sessions the research team provided guidance, but teachers were given autonomy to interact with the GenAI directly. To support them, teachers were given a structured set of elements to address: a negotiated definition of a rich task; task duration; curriculum outcomes; a warm-up task; learning intentions and success criteria; opportunities for explicit teaching; a resource list; enabling and extending prompts; differentiation ideas; reflection prompts; an assessment rubric; and a word list. These served as a scaffold to guide interactions with the AI while providing flexibility.

Teachers were observed across three lessons corresponding to the three tasks. Observations were conducted by both authors, recording detailed notes using an observation schedule. Student focus groups of up to six students (teacher selected) were conducted following implementation, with each class participating in at least one focus group session per case.

Following data collection, all sources were collated and prepared for analysis. Interviews and focus groups were transcribed verbatim, and GenAI planning logs and artefacts were formatted with attention to teacher prompts. The full dataset was imported into NVivo 15, where a coding framework grounded in the three theoretical lenses was applied. Researchers first coded the broader dataset independently then collaboratively, reviewing codes to ensure consistency. For the three cases reported here, data were coded independently and then analysed comparatively to identify patterns and variation in AI implementation and task quality.

To address the research aims and capture the complexities and nuances of AI uptake, teacher planning, and classroom practice, three theoretical frameworks were applied to the data. First, the Technology Acceptance Model (TAM) (Davis, 1989) was used as the 'adoption' lens to help us understand teachers' perceptions of the value of generative AI and their attitudes and intentions for future use. The TPACK Developmental Model developed by Niess et al., (Niess et al., 2009) was used as a 'practice' lens alongside TAM to identify how the teachers used the generative AI along with the level of assimilation of the tool into their teaching practices.

Finally, the Mathematical Knowledge for Teaching (MKT) model (Ball et al., 2008) assisted us as the 'mathematics and pedagogy' lens in investigating the depth of mathematics knowledge required to ensure teachers' interactions with the generative AI produced tasks that were appropriate and of high quality.

## Findings and Discussion

To address the research questions, we first examine findings related to the design and classroom enactment of the three rich tasks. We then analyse the broader impact of using GenAI as a planning tool for the three teachers and their students.

### Task Design using GenAI

As detailed, the participating teachers were at different career stages and had varying prior experience with GenAI. Analysed through the Technology Acceptance Model (TAM) (Davis, 1989), all three demonstrated sustained positive attitudes towards AI use. Teachers reported strong perceived usefulness for rich task development through AI, and for Tania and Audrey, perceived ease of use translated into ongoing behavioural intention, with continued use across mathematics and other areas. These findings suggest that technological resistance was not a primary barrier; rather, the critical work occurred at the pedagogical level.

Viewed through the TPACK Development model (Niess et al., 2009), participation appeared to shift teachers' integration of AI within their pedagogical practice. Tania and Olivia began at the Accepting phase, consistent with their voluntary participation. Tania was already experimenting and was in the Adapting phase as described by Niess et al. On conclusion of the study, Audrey and Olivia had moved toward the Exploring phase, recognising how GenAI had extended their pedagogical repertoire, as evidenced in Olivia's reflection: "There's so many things that I think I needed to contextually base the lesson more, and that can be done using AI...", in contrast to the findings of Walkington (2025). Similarly, Audrey described increasingly strategic prompting to contextualise tasks and further differentiate learning: "...if I'm not happy with one or two questions, then I would put it through again. 'Can you differentiate this question and include students with mixed abilities?' It's easy."

While TAM and TPACK assist in explaining adoption and developmental progression, the MKT framework (Ball et al., 2008) illuminates how teachers mediated AI-generated suggestions through professional judgements during task design. Knowledge of Content and Curriculum (KCC) played a particularly important role during planning. Although the teachers entered specific curriculum content descriptions for each lesson, they were at times required to prompt the AI to modify the content when it did not align with the curriculum requirements.

Knowledge of Content and Students (KCS) was evidenced in a planning discussion between the research team and Olivia regarding her lesson on chance and probability. When ChatGPT suggested students construct their own spinners, Olivia initially considered using a virtual spinner via PolyPad for reasons of efficiency. However, she ultimately decided that having students physically create their own spinners would enhance their conceptual understanding of randomness and probability, while PolyPad could be used to explore variations in likelihood or to conduct extended experiments. This episode illustrates how KCS informed pedagogical decision-making in ways that mediated the AI-generated suggestions.

Further evidence of KCS and Knowledge of Content and Teaching (KCT) emerged in the adaptations Audrey made between planning and implementation. She initially modified her 'Decimal Dilemma at the Market' task by personalising it as 'Audrey's Ice-Cream Parlour', replacing the suggested fictional market price list from the NSEduChat lesson output: ("Provide students with a fictional market price list that includes items priced in whole numbers and decimals") with a context she believed would increase student engagement. This provided a context for explicit modelling prior to independent problem solving. She then extended the lesson beyond the AI-generated structure by incorporating real Woolworths supermarket catalogues. This additional task required students to apply their understanding of decimals to select healthy snacks within a given budget.

Similarly, Tania negotiated with NSWEduChat during task design, prompting: "I said I would prefer Play-Doh. 'Can you give me a lesson with Play-Doh?' And that's what it came out with." Her request reflected a judgement about the practical suitability and appropriateness of materials for her class, shaping the AI-generated task to better align with her students' needs and the realities of her classroom context. Together, these modifications illustrate KCS in anticipating how particular materials and contexts would function for specific learners, and KCT in the deliberate selection and structuring of tasks to support conceptual development.

While the planning phase illustrated how the teachers mediated GenAI through their MKT, its role became more complex during implementation. Task design decisions were further shaped by real-time pedagogical judgement and student responses. The following section examines how AI-supported tasks were implemented in practice and how teachers' professional knowledge continued to shape their enactment.

## Classroom Enactment of AI-Generated Rich Tasks

Classroom observations of the rich task implementation made visible the central role of MKT in mediating how AI-supported tasks were enacted in practice. Across all three lessons, the teachers were observed making in-the-moment decisions in response to student thinking, an aspect they later acknowledged in their final interviews.

In Audrey's lesson, many adaptations were observed. These changes reflected her depth of MKT and her recognition of the teaching and learning opportunities embedded within the rich task. Audrey made this comment in relation to her enactment of the task:

> *You have the time component, you still have explicit teaching, but it's up to the teacher how you're going to do your delivery... It's not really part of the activity, it's written there. But when I did my lessons, I always focused on vocab because from experience, that's a big thing in my class.*

*Such real-time pedagogical adjustments* cannot be anticipated by AI. Pedagogical decisions such as if and how students are grouped, potential responses to student misconceptions, or specific questioning techniques are dependent on the teacher's knowledge. This was evident in Tania's lesson where she adapted the task in the moment, explaining, "Well, it was just off the cuff. I saw that one of the kids wanted to know...that comes with just being a teacher for so long". This comment highlights the role of accumulated experiential knowledge within MKT.

In contrast, fewer pedagogical adjustments were observed in Olivia's lesson. During the lesson, the construction of physical spinners appeared to shift students' attention towards the craft elements of the activity rather than the intended mathematical focus. No pedagogical shifts were made to address this during the lesson. However, her final interview, Olivia reflected:

> I felt like for that group of children, it just kind of was about the spinners…Upon reflection, I would've done a virtual spinner just because I feel like it was very overwhelming for them to be cutting out or and colouring...It kind of took away from the maths…I should have done it digitally and had the confidence to maybe alter that with AI.

Olivia's reflection demonstrates emerging professional judgement, suggesting that while the pedagogical implications were not fully recognised in the moment, they became visible through post-lesson reflection. In this way, the enactment phase further illustrates how MKT shapes not only immediate instructional decisions, but also teachers' ongoing professional development.

In Olivia's lesson, some of these affordances were not taken up during implementation. For example, students constructed pre-printed spinners divided into equal sections, which limited opportunities to explore unequal partitions and their probabilistic implications. Similarly, potential connections to angle measurement and to addressing emerging misconceptions during the reflection phase were not pursued in the moment. Importantly, these observations are not presented as a critique of individual practice. Rather, they underscore that recognising and capitalising on the mathematical richness of tasks, particularly those generated or supported by AI, depends on teachers' ongoing development of MKT. As such, the findings highlight the importance of sustained professional learning to support teachers in identifying and enacting the full range of mathematical possibilities embedded within AI-generated rich tasks.

A significant observation arising from the comparison of classroom enactments with the original GenAI outputs was the variation in how teachers recognised and leveraged the mathematical 'richness' embedded within the tasks. Audrey and Tania frequently paused to provide explicit instruction, extend discussion, and adapt the tasks to deepen student thinking across multiple mathematical concepts. Their enactment reflected well-developed Specialised Content Knowledge (SCK), KCS, and KCT, particularly in identifying moments where mathematical ideas could be made more explicit.

## Implications for Teachers

The use of GenAI to design rich tasks presents both opportunities and responsibilities for teachers of primary mathematics. Participants reported that AI generated fresh ideas, particularly for experienced teachers such as Tania and Audrey. A key affordance was the capacity to tailor tasks through deliberate prompting. As Audrey noted, she could adapt tasks to suit her class rather than rely on existing published resources: "I could make it something that they're familiar with rather than having the general terms as used in the department units."

However, contextualising a task to a specific classroom extends beyond embedding it in a familiar scenario. It requires deep KCS, including awareness of prior understanding, likely misconceptions, and classroom dynamics. While teachers can input contextual details, AI cannot comprehend the nuanced realities of a live classroom. As Olivia reflected, teachers must pause and ask if a task truly fits their context rather than accepting the first output generated.

Prompt crafting therefore emerges as a contemporary enactment of MKT within digitally mediated planning environments, a finding that complements those of Biton et al., (2025). Knowing what to ask of the AI is itself a pedagogical act, requiring clarity about mathematical intentions and anticipated student responses. The quality of AI-generated tasks is shaped less by the tool and more by the professional knowledge within the prompts that guide it.

Teachers also identified practical considerations, including unrealistic time allocations within AI-generated lessons. This reinforced the need for teachers to critically interpret outputs, adjust expectations, and revisit plans prior to implementation. Although all three teachers agreed that refined prompting could significantly reduce planning workload, they cautioned that efficiency must not replace professional judgement. As Audrey noted, AI is only as useful as a teacher's capacity to 'unpack' the activity, and Tania similarly warned that without strong pedagogical knowledge, AI-generated tasks risk lacking depth.

While GenAI expands planning possibilities and may reduce workload, its pedagogical value remains contingent upon teachers' MKT and their willingness to actively negotiate, refine, and take ownership of AI outputs. These teacher-level implications have important consequences for students' engagement and experiences of differentiated learning.

## Implications for Students

The teacher-level implications of GenAI use were reflected in students' classroom experiences. Across the three cases, in alignment with the findings from Rutherford et al., (2025), AI-supported tasks were associated with heightened engagement, particularly when teachers actively adapted and contextualised tasks in response to student needs. During lesson observations and focus groups, students expressed enthusiasm for tasks connected to familiar contexts, with one student commenting, "It was fun, and we could understand it. It was creative and we're still learning" (Focus Group, Case A). The hands-on and creative elements embedded within the tasks were also noted as distinct from students' typical mathematics lessons, particularly in Olivia's class.

At the same time, students in all three classes expressed a desire for greater differentiation. In Audrey's class, a student reflected, "I would've changed the difficulty level because I think most people found it pretty easy and the people who found it hard only struggled with a few bits". Similarly, students in Tania's and Olivia's classes suggested that additional challenge or extension opportunities would have strengthened the tasks. These comments indicate that while engagement was high, not all learners experienced an optimal level of cognitive demand.

Students also recognised that the rich tasks integrated multiple mathematical ideas. As one student in Audrey's class observed, "It's different because we usually just do one topic for math, but today we did a bit more…". This suggests that AI-mediated task design has the potential to support more connected and conceptually integrated mathematical experiences. However, the extent to which these affordances translate into deep learning remains dependent upon how effectively teachers refine and differentiate the tasks during planning and enactment.

## Conclusion

This paper reports on three cases only and does not claim broad generalisability. However, the combined use of TAM, the TPACK Development Model, and MKT enabled a layered analysis of AI adoption, pedagogical development, and classroom enactment. Across cases, findings show that while GenAI expands possibilities for task design and planning efficiency, its impact is neither automatic nor uniform.

The effectiveness of AI-supported rich tasks was mediated by teachers' MKT. Teachers who crafted intentional prompts, critically evaluated outputs, and adapted tasks responsively enhanced enactment and student engagement. Although students valued contextualised and conceptually connected tasks, their call for greater differentiation reinforces that meaningful learning depends on sustained teacher expertise rather than technological capability alone.

While GenAI may reduce workload and broaden pedagogical options, its value remains contingent upon teachers' professional knowledge and confidence to negotiate, rather than accept, AI outputs. Further research is needed to identify effective professional learning approaches and clarify the conditions under which AI may enhance student outcomes. Ultimately, GenAI does not diminish teacher expertise; rather, it repositions MKT as the decisive factor in determining whether AI-supported task design enhances or constrains meaningful mathematical learning.

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