

Monetisation Models for Academic Creators: A Mixed-Methods Study of 997 Doctorate-Signed Newsletters and 92 Public Discussion Threads

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Abstract

Scholars who publish for the public increasingly try to earn from that work, and generative AI tools promise to cut the hours it takes. This study proposes a mixed-methods framework for describing how academic creators monetise their expertise and how AI tools could change the economics, and applies it to public evidence. A quantitative strand classified the latest posts of 174,656 active newsletters on a large publishing platform, 997 of them signed by authors with a doctoral or professorial title; a qualitative strand coded 92 public question threads with 357 answers in which academics discussed earning from their expertise. One doctorate-signed newsletter in five mentioned an offer of its own, more often than other newsletters in the same topic category (odds ratio 1.47), usually through a single model such as books, courses or paid membership, whereas sponsorship and donations were rare. AI was discussed by 31% of the doctorate-signed newsletters, but only 0.6% described using it in their own work, and naming AI tools was not associated with more offers or more frequent posting. The threads raised employer policy, ethics and tax as the main concerns, and AI appeared in only one of them. A labelled planning simulation suggests that AI drafting mainly saves hours rather than raising income, and pays off most for creators with little time. A protocol for the survey and interviews, with their sample sizes, is proposed.

Keywords: creator economy; academic entrepreneurship; monetisation; newsletters; generative AI; mixed methods

1. Introduction

Many academics now share their expertise with the public through newsletters, videos, podcasts and short courses, and a growing number try to turn that audience into income [1,2]. Membership platforms, online course markets and paid newsletters have made such offers easy to set up [3,4]. Universities, in turn, encourage public engagement and entrepreneurial activity by their staff [5,6]. Here an academic creator is a scholar who publishes for a public audience under their own name and offers something in return for payment. Little is known, however, about which monetisation models academic creators actually use, how often they use them and what holds them back [7].

Generative AI adds a new question. Writing experiments show that language models shorten drafting substantially [8,9]. AI tools are already used to produce marketing content and social media posts [10]. If AI tools cut the hours needed per issue or module, they could change which models pay; if they lower quality or trust, they could erode the audience every model depends on [11].

This paper asks which monetisation models academic creators use and how AI tools could change their economics. It proposes a mixed-methods framework that combines public newsletter

posts, public discussions among academics and a labelled planning simulation of income and hours. The survey and interviews that the question ultimately requires are specified as a protocol.

2. Background and Literature

2.1 The Creator Economy and Its Business Models

Research on the creator economy describes platforms that match creators with audiences and share revenue through advertising, subscriptions and tips [1,4]. On membership platforms, a small share of creators earns most of the income and steady support depends on regular output [3], and in crowdfunding the quality of the offer and the creator's network predict success [12,13]. Early crowdfunding research also found that visible preparation signals quality to backers [14]. Digital business models in small firms rely on search visibility, pricing and platform choice [15,16].

2.2 Academic Engagement and Academic Creators

Academic engagement with industry and the public, from consulting to contract research and talks, is common and accompanies productive research rather than replacing it [5]. Earlier work found such engagement more common among senior and well-funded researchers [17]. Science communicators on video platforms gain audiences through personal and regular formats [2,18]. Question-and-answer communities have been studied as durable records of practical expertise [19]. Education research describes edupreneurship, in which lecturers build creative, journalistic and entrepreneurial skills into teaching [6,7,20]. Online courses have also been analysed as business models [21].

2.3 Generative AI and Content Work

Generative AI is changing content work. It raises writing productivity [8,9]. It is also used to create marketing and educational content [10,22]. However, it can produce confident errors [11], and it raises ethical questions in higher education [23,24]. AI is also being built into business model innovation in start-ups and entrepreneurial firms [25]. Few studies, however, observe what academic creators offer and how they talk about AI in the same population, which is the gap addressed here. Design science provides the frame for proposing and evaluating such a framework [26].

3. Method

3.1 Design

The study follows a convergent mixed-methods design in which a quantitative and a qualitative strand are analysed separately and integrated in a joint display [27]. Fig. 1 shows the proposed framework. A labelled planning simulation then links the observed models to income and hours with and without AI tools, and the survey and interviews that would test the framework directly are planned but not yet carried out [28].

3.2 Quantitative Strand: Newsletter Posts

The quantitative strand used an openly released dataset of 3.5 million posts from public newsletters on a large publishing platform, collected from public feeds and published under a Creative Commons attribution licence. It was released in 2026 with a persistent identifier and downloaded on 18 October 2026; its posts span 2008 to September 2026, but 82% date from 2025 or 2026 because feeds expose only recent posts. It holds up to the 20 latest posts of each newsletter with title, summary, author, date and topic category. Newsletters with at least ten posts and a post since 2020 were kept, 174,656 in total. A newsletter counted as doctorate-signed when its author name

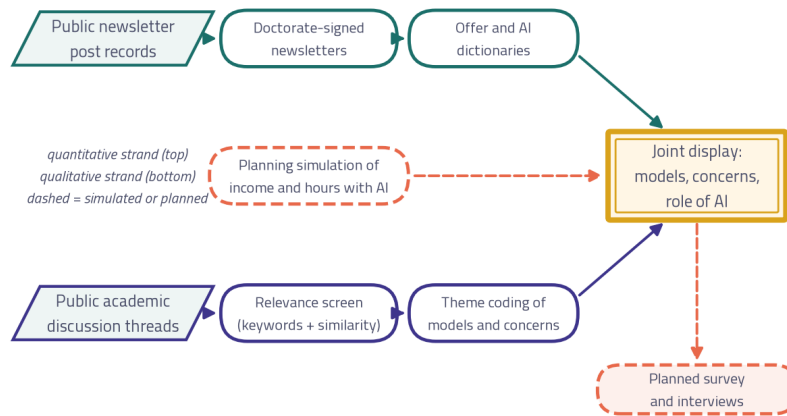


Figure 1. The proposed mixed-methods framework: a quantitative strand on newsletter posts and a qualitative strand on discussion threads meet in a joint display of models, concerns and the role of AI; dashed elements are simulated or planned.

carried a doctoral or professorial title, which gave 997 newsletters; 1,563 signed only with a doctor title, which also covers medical doctors, were analysed as a separate group. Author names were used only to set these flags and were then replaced by one-way hashes, so no creator is named in the results. Exact repeats were also checked: 164 posts repeated within a newsletter and 6,369 titles shared across newsletters made up under 0.5% of posts and were kept, since no model was trained or tested.

Offers were identified by keyword dictionaries applied to post titles and summaries for six models: paid membership, courses or workshops, consulting or coaching, books or other products, sponsorship and donations [3, 16]. The phrase ‘of course’ was removed before matching, and course terms required a qualifier such as ‘my’, ‘new’ or ‘online’. A reading check of 15 random matches per class among doctorate-signed newsletters counted how many referred to the author’s own offer. Further dictionaries marked posts that discussed AI, named AI tools and described the author’s own use of AI. Posting frequency was the number of posts per week across the recent window, and a newsletter was active when it had posted in the last 90 days of the data, that is, after 30 June 2026. Associations were estimated with logistic and linear models adjusted for topic category. Because many associations were examined, p-values are descriptive and only intervals that exclude one are interpreted.

3.3 Qualitative Strand: Public Discussion Threads

The qualitative strand used a public question-and-answer site on which academics ask and answer questions about academic life, whose content is published under Creative Commons attribution share-alike licences. Questions were retrieved through the public interface of the site with keyword and tag searches, and were kept when they mentioned both earning and an expertise-based activity and were close in meaning to three descriptions of academics earning from expertise in a sentence-embedding space. This gave 92 questions from 2012 to 2026 with 357 answers. They came from 75 different askers and were viewed 490,247 times in total; the similarity threshold of 0.35 was fixed before coding by reading the titles around it. Each thread was coded with a dictionary for eight models and six concerns [29]. As a check, a second coding assigned each question that named exactly one model to the nearest of eight model descriptions in the embedding space [30]. No user names were stored, and no one was contacted.

3.4 Planning Simulation (Assumed Values, Not Observed Data)

The simulation is a labelled planning exercise with assumed values. A creator with six hours a week and an audience of 500 free readers runs one of four models for 24 months: paid membership with a weekly issue, a course of eight modules, consulting, or a course combined with consulting. AI tools are assumed to save 35% of drafting time, to cost 20 US dollars a month and to lower the audience's response by 5%, and each scenario was run 500 times with uncertain parameters (Table 1) [8,31]. Members were assumed to be 4% of the audience at 6 US dollars a month, course buyers 0.4% a month at 90 dollars and consulting demand 0.4% at 120 dollars an hour with one hour of preparation, after platform fees of 15%. Each parameter was then varied one at a time over a plausible range.

Table 1. Labelled planning simulation of 24 months of four monetisation models with human or AI-assisted drafting (means of 500 runs). All parameters are assumptions.

Model	Income, month 24 (USD)	Hours per week	Income per hour (USD)
Paid membership, human	223	4.0	9.2
Paid membership, AI-assisted	196	2.5	12.4
Course, human	242	2.8	13.9
Course, AI-assisted	202	1.8	20.1
Consulting, human	362	3.0	22.6
Consulting, AI-assisted	331	2.1	29.4
Course and consulting, human	611	3.8	25.7
Course and consulting, AI-assisted	580	2.6	38.4

4. Results

4.1 Offers in Doctorate-Signed Newsletters

Doctorate-signed newsletters mentioned an offer of their own more often than other newsletters (Fig. 2). Among the 997, 20.4% mentioned at least one offer in their recent posts, compared with 14.5% of other newsletters, an odds ratio of 1.47 (95% interval 1.26 to 1.72) within the same topic category. Books and other products were the most common model (7.1%), followed by courses or workshops (6.2%), paid membership (5.4%) and consulting or coaching (3.8%), while sponsorship (0.8%) and donations (0.2%) were rare [3]. Paid membership showed the largest difference from other newsletters (odds ratio 1.81, 1.37 to 2.38), followed by books (1.49) and courses (1.38), whereas consulting did not differ clearly (1.38, 0.99 to 1.91). In the reading check, 14 of 15 membership matches, 11 of 15 book matches, 9 of 15 course matches but only 4 of 15 consulting matches referred to the author's own offer (Fig. 6). Corrected for precision, the shares would be about 5.1% for membership, 5.2% for books, 3.7% for courses and 1.0% for consulting. Newsletters signed only with a doctor title also mentioned offers more often than others (odds ratio 1.46, 1.28 to 1.65). Restricting the comparison to the 815 doctorate-signed newsletters with a full window of 20 posts gave the same result (1.45, 1.23 to 1.72), whereas matching titles alone lowered every share, to 2.0% for membership, 2.8% for courses and 3.5% for books, so most mentions appear in summaries. Most creators relied on one model: of the 203 newsletters with an offer, 175 mentioned only one [1]. The most frequent combinations were membership with books (6), courses with books (6) and courses with consulting (5) (Fig. 5).

4.2 AI in Doctorate-Signed Newsletters

Doctorate-signed newsletters also wrote about AI more often: 31.0% discussed AI, against 21.2% of other newsletters (odds ratio 1.56), and 8.8% named specific AI tools, against 6.5% (odds ratio 1.21, 0.96 to 1.52). Only six of the 997, or 0.6%, described using AI in their own writing or research. Naming AI tools was not associated with offers among academics (Fig. 4): 15.9%

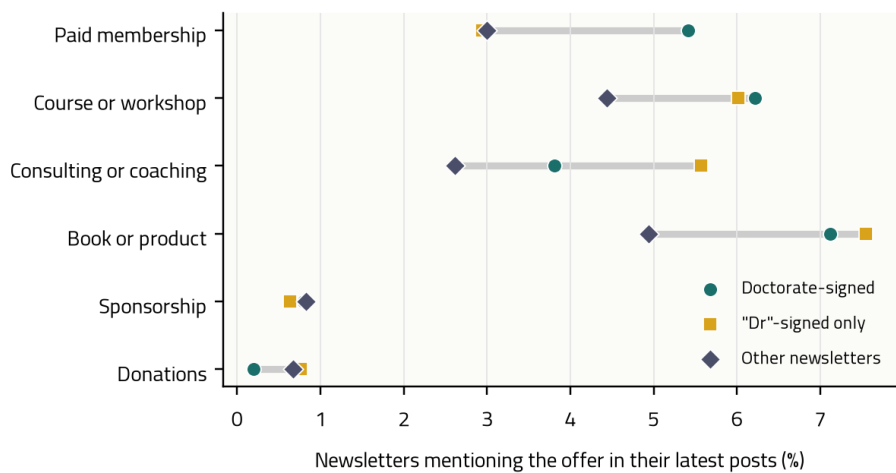


Figure 2. Cleveland dot plot of the share of newsletters mentioning each monetisation offer in their recent posts, for doctorate-signed newsletters, newsletters signed only with a doctor title and all others.

of those that named tools mentioned an offer, against 20.8% of the rest (Fisher $p = 0.33$). Nor did they post more often, with a ratio of 0.91 (0.73 to 1.15) in posting frequency. Naming AI tools was concentrated in the technology category, where 22% of doctorate-signed and 18% of other newsletters did so, against 4% in general newsletters (Fig. 8). Across all newsletters, those naming AI tools mentioned courses (odds ratio 1.48) and consulting (1.44) more often but posted slightly less often (ratio 0.96, 0.94 to 0.98) .



Figure 3. Balloon plot of the concerns raised in public discussion threads about each monetisation model; numbers give the percentage of threads on the model that raise the concern, with the number of threads in brackets.

4.3 Activity and Posting Frequency

Of the doctorate-signed newsletters, 76.5% were still active in the last 90 days, against 68.8% of others. They also posted a median of 0.59 times a week against 0.50, and slightly more often across the whole distribution (Fig. 7). Newsletters that mentioned an offer were more often still active (odds ratio 1.16, 1.12 to 1.19), adjusted for posting frequency and category. Offers may simply mark newsletters that would have continued anyway, so this association is not evidence that offers sustain a newsletter.

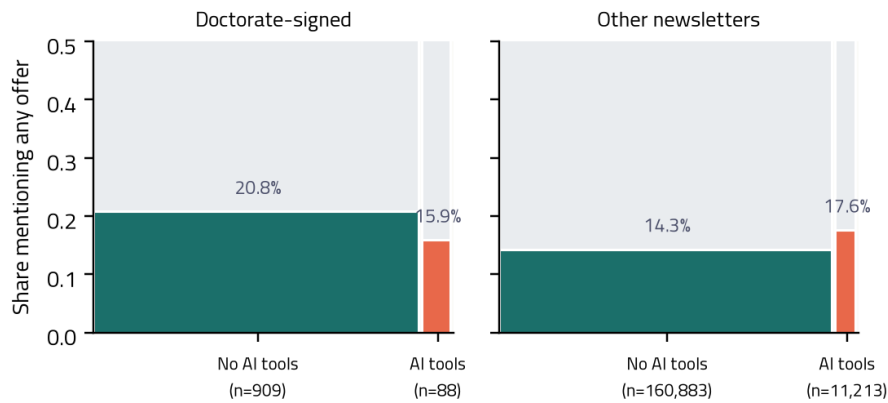


Figure 4. Spine plots of the share of newsletters mentioning any offer by whether they named AI tools, for doctorate-signed and other newsletters; column widths are proportional to group size.

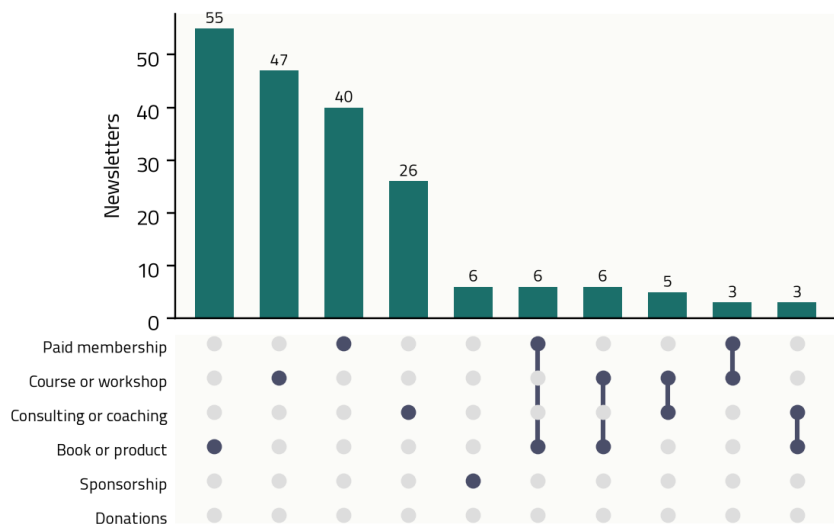


Figure 5. UpSet plot of the ten most frequent combinations of offers among doctorate-signed newsletters; bars give the number of newsletters and dots the models combined.



Figure 6. Icon array of the reading check: of 15 random matches per class, filled circles referred to the author's own offer.

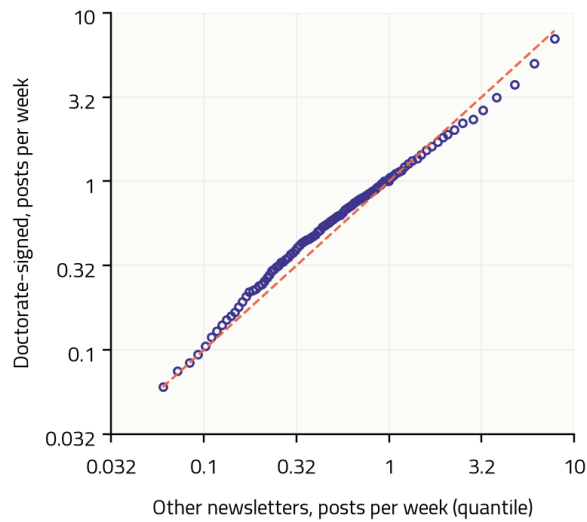


Figure 7. Quantile-quantile plot of posts per week, doctorate-signed against other newsletters, on log scales; the dashed line marks equal distributions.

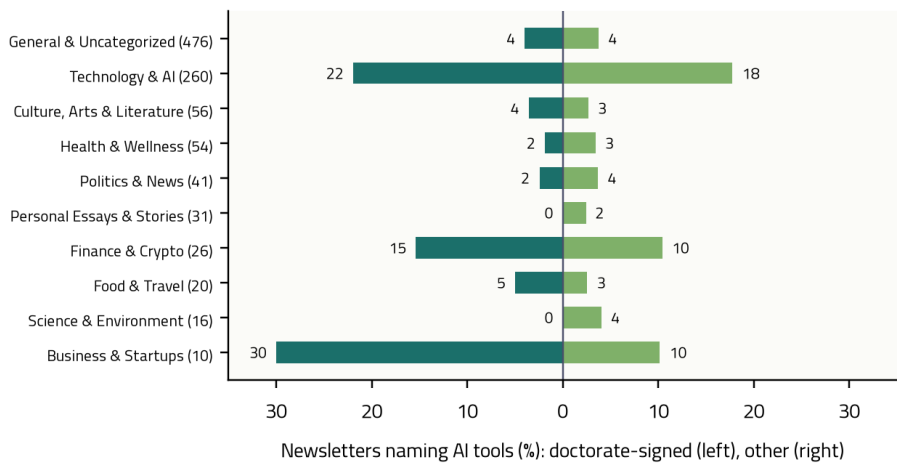


Figure 8. Back-to-back bars of the share of newsletters naming AI tools by topic category, doctorate-signed (left) and other (right); the number of doctorate-signed newsletters is in brackets.

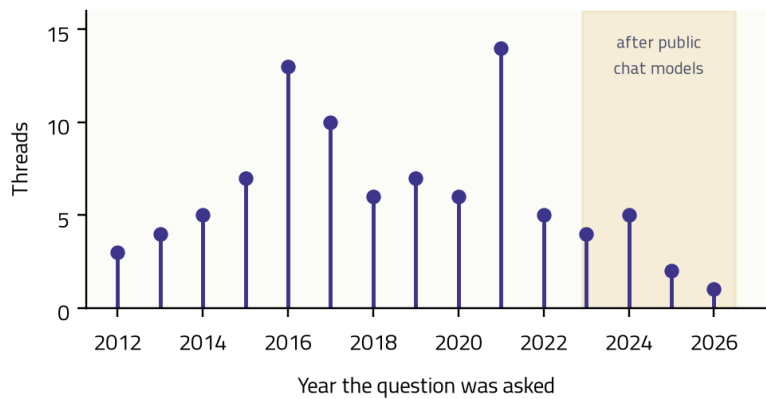


Figure 9. Stem plot of the discussion threads by the year the question was asked; the shaded band marks the years since public chat models became widely available.

4.4 Public Discussion Threads

The threads drew a median of 1,969 views, so the concerns they raise reach a wide academic audience. Questions most often concerned books and textbooks (41%), software and start-ups (27%), videos, blogs and podcasts (23%) and private tutoring (17%), while consulting (13%), donations (10%), courses and lecture notes (9%) and paid talks (3%) were less frequent [5]. Across questions and answers, the most frequent concerns were employer policy and ownership of the work (52% of threads), ethics and conflicts of interest (41%), tax and legal questions (35%) and time (35%), while 30% invoked the ethos of open access (Fig. 3). Ethical concerns dominated threads on tutoring (69%) and courses (62%), time dominated consulting (58%), and employer policy dominated donations (89%). AI was mentioned in only one of the 92 threads, and in none of the 12 threads started since 2023 (Fig. 9) [29]. The second coding agreed with the keyword coding on 76% of 50 single-model questions (Cohen's kappa 0.67).

4.5 Planning Simulation Results (Simulated, Not Observed)

In the planning simulation (Table 1), AI-assisted drafting reduced weekly hours by about a third in every model but did not raise income. Monthly income after 24 months was slightly lower with AI tools because of the tool cost and the assumed lower response, whereas income per hour rose in every model, most for the combination of a course and consulting, from 25.7 to 38.4 US dollars [9]. Over the 24 months the income paths with and without AI overlapped widely (Fig. 10), and income per hour varied between runs but shifted upward with AI in every model (Fig. 12). The result depended most on the creator's time (Fig. 11): with three hours a week, AI tools added about 4,570 US dollars over 24 months because the course was finished sooner, whereas with ten hours they cost about 620 dollars. A quality factor of 0.85 instead of 0.95 turned the small base loss of 146 dollars into a loss of 1,150, and a tool cost of 60 dollars a month into a loss of 1,106.

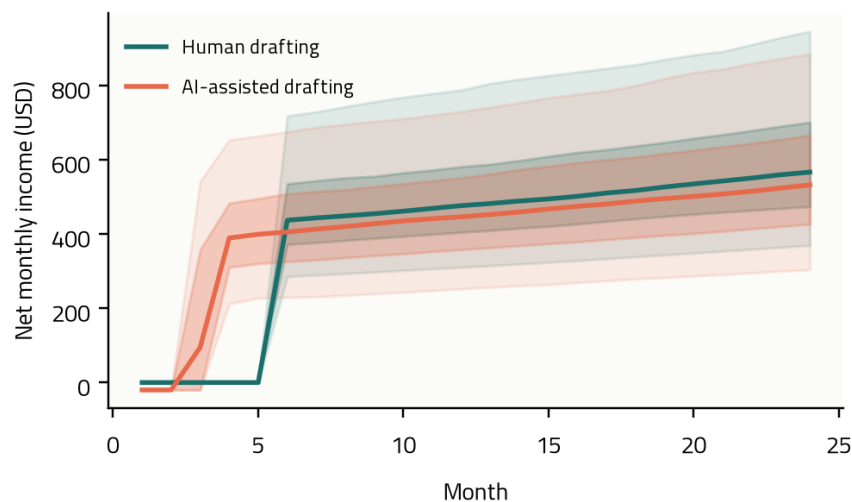


Figure 10. Planning simulation: fan chart of net monthly income for a course combined with consulting, with medians and 50% and 90% bands, for human and AI-assisted drafting.

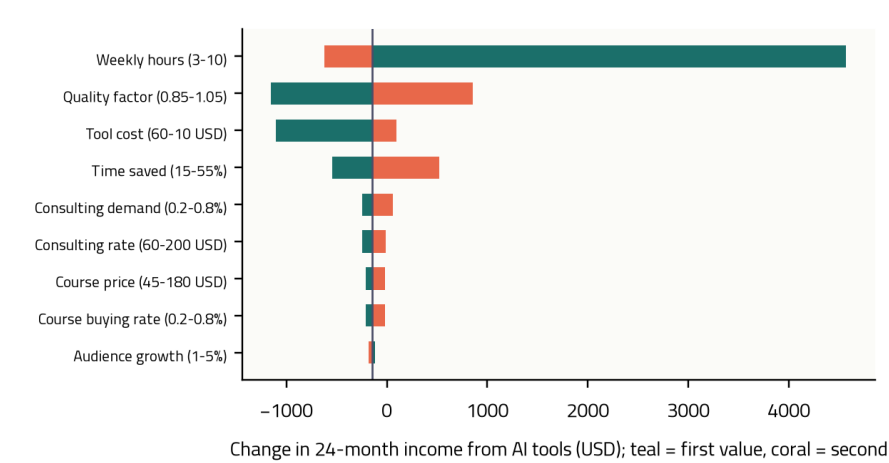


Figure 11. Planning simulation: tornado chart of the change in 24-month income from AI tools when each assumption is set to a low or high value.

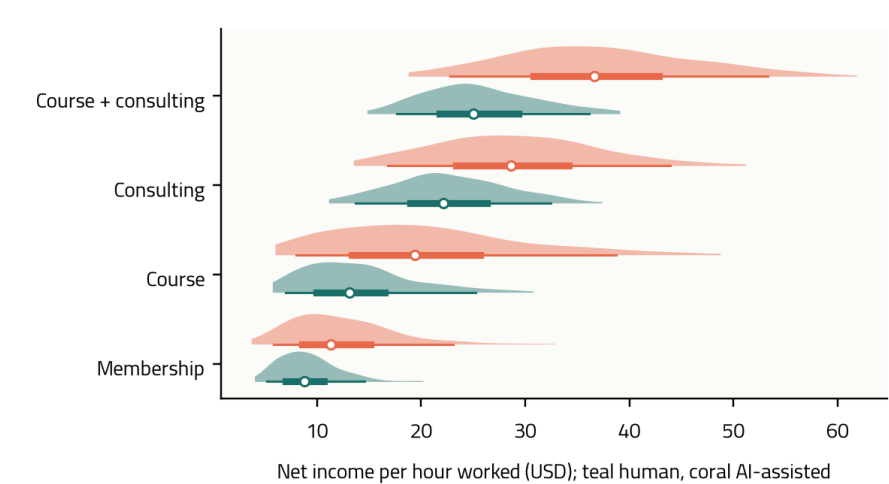


Figure 12. Planning simulation: half-eye plots of net income per hour by model for human and AI-assisted drafting, with medians, 50% and 90% intervals.

5. Discussion

5.1 Models and Concerns

Academic creators monetise their expertise through a narrow set of models. Books, courses and paid membership dominate, consulting is less visible in public posts, and sponsorship and donations are almost absent, so scholars sell what resembles teaching and publishing rather than attention [5]. Doctorate-signed newsletters mentioned offers more often than others in the same category, so an academic title appears to support paid offers, perhaps by signalling expertise [32,33]. The doctor-signed group, which includes medical doctors, showed the same pattern, so the effect is not specific to research degrees. Read together, the two strands agree that teaching- and publishing-like models dominate, and the threads add the institutional reasons why consulting and donations remain less visible [27].

Most creators rely on a single model, and the threads suggest why: each model brings its own concern, from ethics when selling to one’s own students to employer rules and the time consulting takes [20]. The ethos of open access, raised in almost a third of the threads, sits uneasily with paywalls, which may explain why books and courses are preferred to membership [2].

5.2 The Role of AI

The role of AI is so far mostly a topic rather than a tool. Academics wrote about AI more than other creators but rarely described using it, and naming AI tools was not linked to more offers or more frequent posting, so there is no sign yet that AI has changed what academic creators produce [8,11]. The simulation suggests why: if AI saves time but slightly lowers response, its benefit appears as hours returned to the creator rather than as income, so it matters most for creators whose time is scarce [31]. The saved hours could also be reinvested in more output, but newsletters that named AI tools did not post more often, so there is no observed sign of such reinvestment.

5.3 Implications for Academic Creators

For an academic creator, the evidence suggests starting with one offer close to teaching or publishing, checking the employer’s rules on outside work and on ownership of course material first, and treating AI tools as a way to save hours rather than as a source of income [34,35]. Selling to one’s own students should be avoided, and AI-drafted material should be disclosed to the audience [36].

6. Proposed Protocol for the Survey and Interviews (Not Yet Carried Out)

The survey and interviews that would test the framework directly have not been carried out. Table 2 sets out the protocol. Its sample sizes come from the labelled planning simulation and are planning figures, not results.

Table 2. Protocol for the planned survey and interviews (not yet carried out); sample sizes come from a labelled planning simulation.

Element	Planned survey and interviews
Population	Academics who publish for the public and sell at least one offer
Survey	About 385 for prevalence within 4 points; 1,200 for an odds ratio of 1.5
Survey items	Models, prices, income, hours, AI tools used and for what
Interviews	About 45, purposive by model and discipline, until no new themes
Interview guide	Start of selling, employer rules, ethics, pricing, AI in production
Ethics	Consent, anonymity, approval first, no payment data stored

A planning simulation shows that about 385 respondents would estimate a 20% prevalence within 4 points, that about 1,200 would be needed to detect an odds ratio of 1.5 between AI users

and others with 80% power, and that about 45 interviews would hear each common model at least twice with 80% probability (Fig. 13) [38,39].

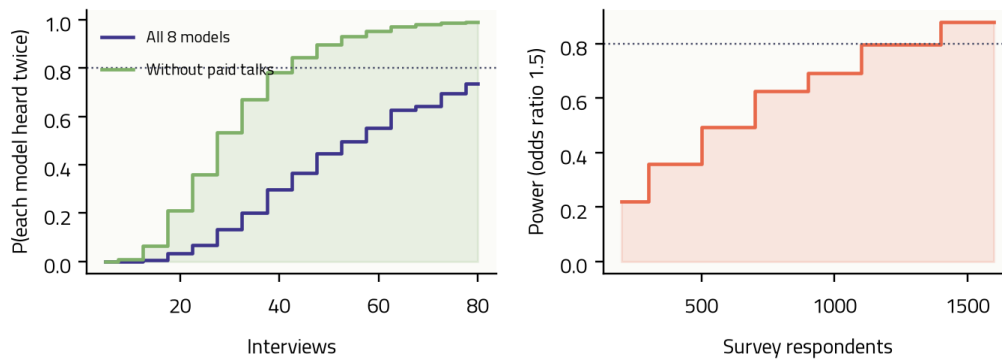


Figure 13. Planning simulation for the protocol in Table 2: probability that every model is heard at least twice by number of interviews (left) and power of the survey to detect an odds ratio of 1.5 (right).

7. Limitations

The study has limits. A title in an author name is a proxy for academic status, mentions of offers are not confirmed sales, and the recent window of each newsletter gives a cross-section rather than a history, in which newsletters active only in earlier years are under-represented. No income, price or audience size is observed for any newsletter, so the economics are known only from the simulation. The dictionaries were checked only by a small reading sample, and the consulting class had low precision. The platform is one of several used by creators, and those who sell mainly through video or course platforms are not covered [37]. The discussion threads are few and self-selected, and the simulation rests entirely on assumptions.

8. Conclusion

This paper proposed a mixed-methods framework for the monetisation models of academic creators and applied it to 174,656 public newsletters and 92 public discussion threads. Academic creators most often mentioned books, courses and paid membership, usually only one of them, and were more likely than other creators to offer something. AI was much discussed but rarely described as used, and was not linked to more offers or output. A labelled simulation suggests that AI tools change the economics of academic creators mainly through the hours they save. The planned survey and interviews in Table 2 would test these findings directly.

Declarations

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Conflict of interest. The authors declare no conflict of interest.

Data availability. The data that support the findings of this study are available from the corresponding author, Rifqi Fahrudin (rifqi.fahrudin@cic.ac.id), upon reasonable request.

Author contributions (CRediT). Rifqi Fahrudin: conceptualization, writing – original draft. Mochamad Heru Riza Chakim: methodology, formal analysis. Tessa Handra: writing – review and editing. All authors read and approved the final manuscript.

Ethics. Not applicable. The study analysed only publicly available content and did not involve human participants; the survey and interviews described in Section 3 are a proposed protocol and no data from them were collected.

Use of generative AI. The authors used AI-based tools to assist with language editing of this manuscript. The authors reviewed and edited all content and take full responsibility for the work.

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