University of Exeter
Business School

OVERCOMING FAILURE IN GENAI STARTUPS: A CLUSTER ANALYSIS USING THE STP FRAMEWORK FOR MARKETING

BEMM466: Executive Summary for Founders & Executive Team

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Background and Objective

Problem statement

Generative AI (GenAI) tools like ChatGPT, Gemini, Claude, and Copilot have become familiar helpers for everyday questions and technical tasks. The market is growing rapidly, approaching $85 billion by 2029 with a yearly growth rate of around 40% (Johnston, 2025). However, more than 90% of GenAI startups struggle to succeed due to constrained resources and poor product–market fit (AI4SP, 2024; CB Insights, 202). Several studies define this failure as resulting from poor product–market fit (Bethlendi et al., 2025) highlighting the need to identify market needs through understanding consumer heterogeneity and finding the right marketing strategies for achieving product–market fit.

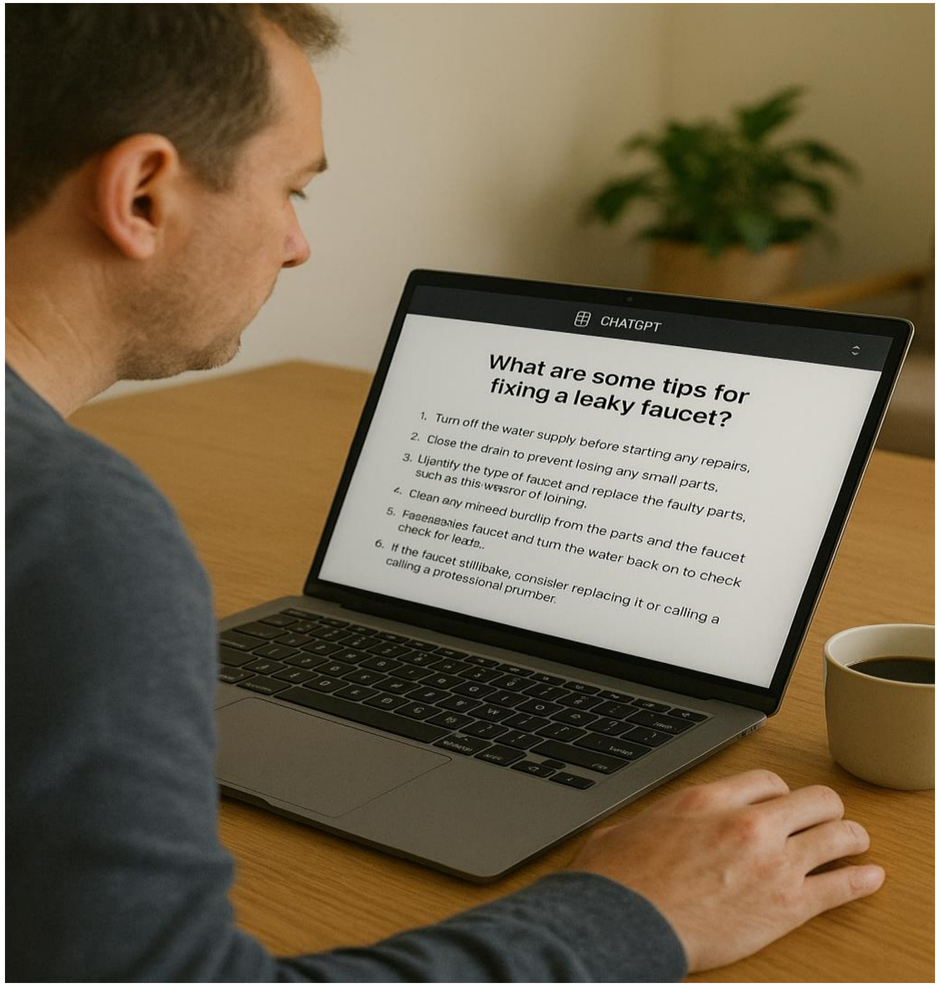
Objective

Therefore, this report will help GenAI startups to:

1. Identify distinct and actionable consumer segments that exist among the UK's GenAI end-users based on their attitudes, behaviours, and concerns about GenAI.

2. Measure which user segment offers the most significant market potential for a generative AI platform, and how the GenAI platform can be positioned to maximise adoption and differentiation.

3. Translate these segmentation insights into marketing strategy (including positioning and a 4Ps marketing mix) to define product-market fits.



(OpenAI, 2025)

* Note all prompt to generated OpenAI image listed in Appendix B

Approach to reach the objective

I have applied the Segmenting–Targeting–Positioning (STP) framework. STP is appropriate for conducting targeting strategies that lead to effective marketing mix tactics. STP consist of:

(Rizzi, 2025)

Segmenting

Organises diverse consumers into meaningful clusters using consumer behaviour, and/or demographics. This will result in a cluster with a similarity preference, and each group is different from others.

Divide consumer

(Day, n.d.)

Targeting

After segmenting, the cluster will be selected based on the plot in the modified GE-matrix with the axes of market attractiveness and adoption readiness.

Pick the right one

(The Indeed Editorial Team 2025)

Positioning

Perceptual mapping is used as a tool to conduct a positioning strategy. The targeted segments are plotted along with GenAI competitors. The mapping reveal the positioning and segment-specific messaging

Win in the right place

(Palmatier & Sridhar, 2021).

Methodology: The STP framework

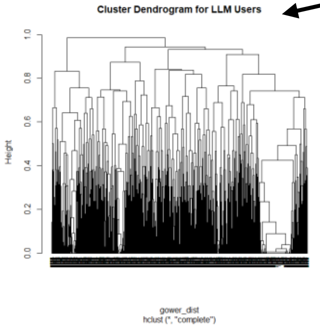
(Rizzi, 2025)

Segmenting

Data source: Ada Lovelace Institute (2024) UK public survey (n=3,513)

Attitude toward Large Language Model (LLM) as a cluster variables

Overall perceived benefits	Perceived benefits by attributes	Overall perceived Concern	Perceived Concern by attributes
1-4 Scale	Binary (Yes/no)	1-4 Scale	Binary (Yes/no)



Hierarchical cluster analysis with Gower distance is used to handle mixed data types.

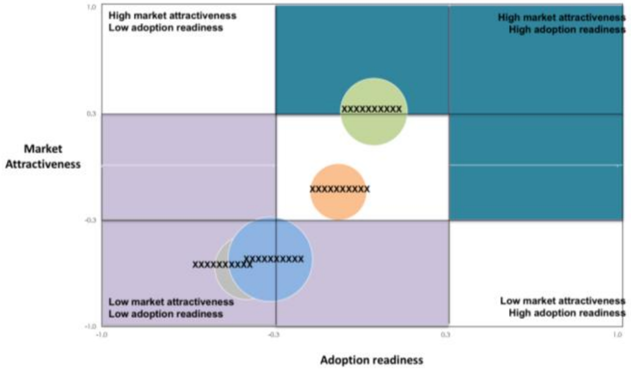
Hierarchical cluster result (Author's work generated by R)

Adding an additional profile to describe the segment:

- Demographic
- Socioeconomic status
- Digital skills
- AI trust factors

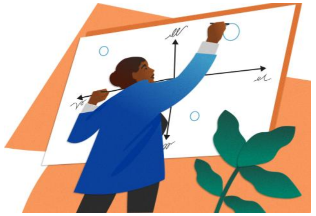
(Day, n.d.)

Targeting



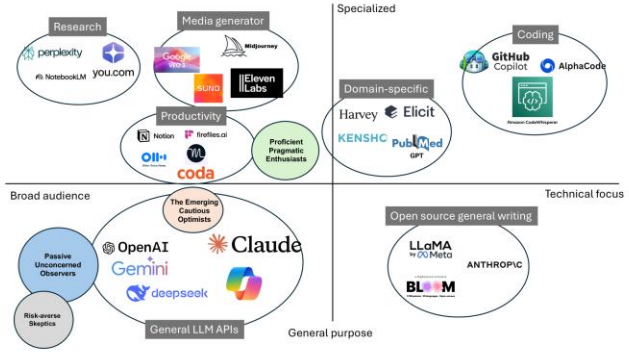
Modified GE matrix (Author's work)

- Each cluster is placed into the modified GE matrix according to its Z-score (standardised) (Andrade, 2021).
- The cluster on the top right represent high opportunity because of high market attractiveness and high adoption rate. Vice versa for the bottom left quadrant.



(Indeed Editorial Team 2025)

Positioning

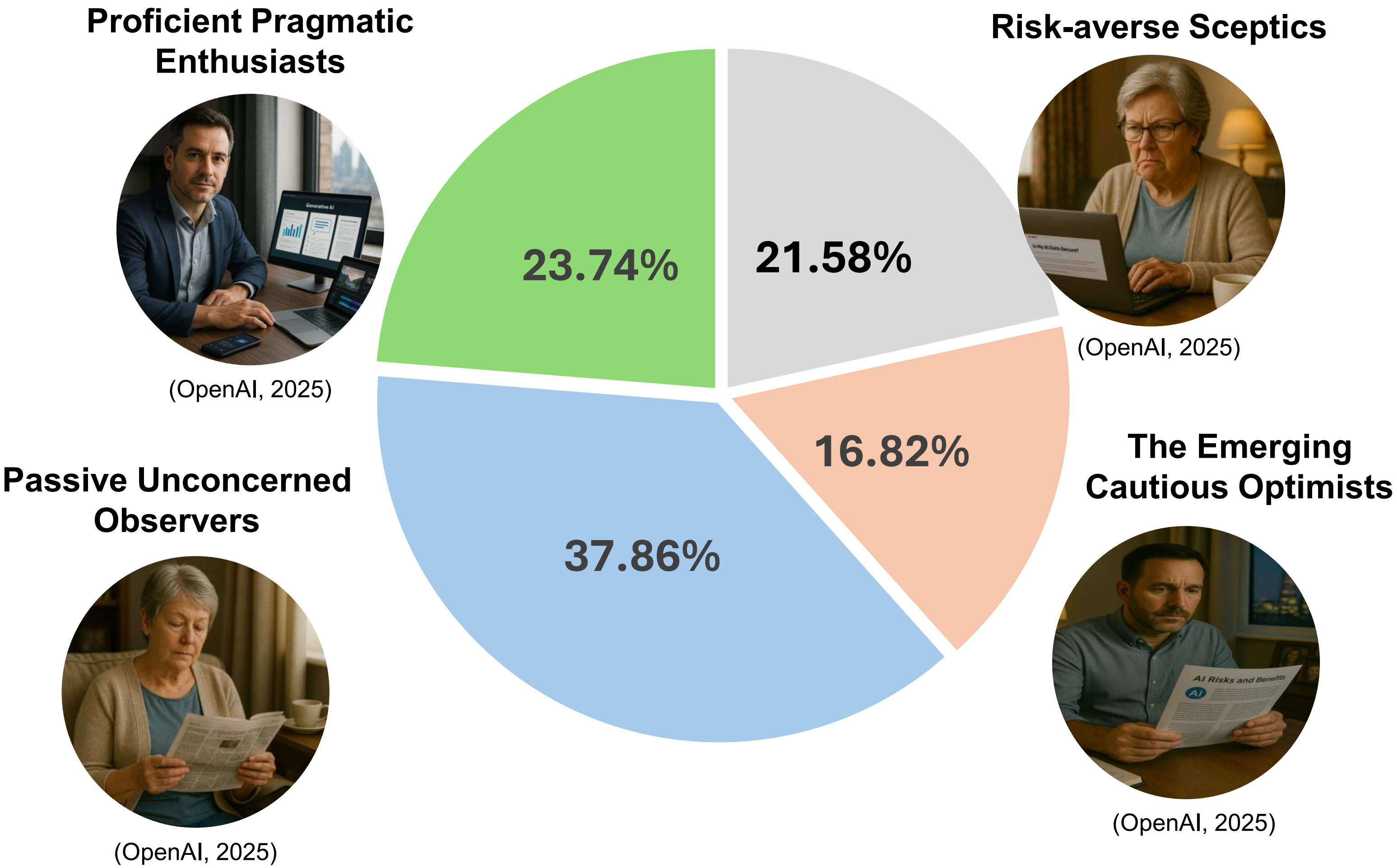


intuitive/judgmental Perceptual mapping (Author's work)

- The targeted segments were then placed in a perceptual mapping with the Y axis representing general purpose to specialised, while the X axis presents a broad audience to a technical focus.

The result of cluster analysis is four distinct segments

The biggest segment is Passive Unconcerned Observers, who represent 37.6% of the total respondents, followed by Proficient Pragmatic and Enthusiasts (23.74%), and Risk-averse Sceptics (21.58%). And lastly, the Emerging Cautious Optimists who account for 16.82%.



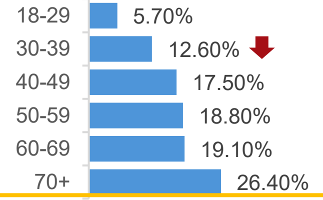
Passive Unconcerned Observers 37.86%:
“I don’t need ‘AI skills’, I’m retired. Email and news are enough.”

↑ Significantly higher than average at 95% confidence level

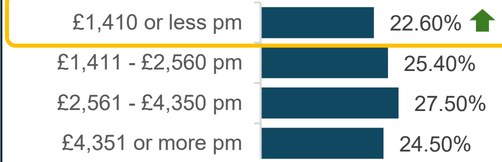
↓ Significantly lower than average at 95% confidence level

(OpenAI, 2025)

Demographic and socioeconomic status

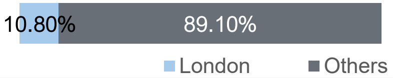


			AVG.
18-29	5.70%		7.4%
30-39	12.60%	↓	15%
40-49	17.50%		17.3%
50-59	18.80%		18.5%
60-69	19.10%		17.9%
70+	26.40%		23.9%



£1,410 or less pm	22.60%	↑	18.7%
£1,411 - £2,560 pm	25.40%		23.75%
£2,561 - £4,350 pm	27.50%		27.61%
£4,351 or more pm	24.50%		29.92%

	CL		AVG.
Managerial & professional occupations	50.2%	↓	56%
Intermediate occupations	11.9%		10.5%
Small employers & own account workers	6.8%		6.7%
Lower supervisory & technical occupations	8.7%		8.8%
Semi-routine & routine occupations	14.9%		12.5%
Not classifiable	7.4%		5.1%



Attitude and behaviour toward GenAI

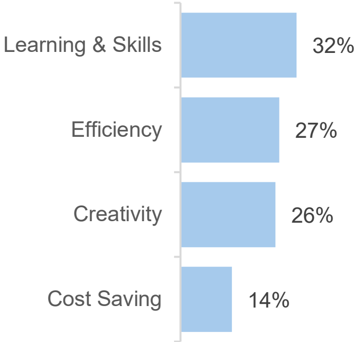
Overall Perceived benefits: Mean: 2.77 ↓ AVG 2.88

Very beneficial = 4
Fairly beneficial = 3
Not very beneficial = 2
Not at all beneficial = 1

Overall Perceived concern: Mean. 2.29 ↓ AVG 2.52

Very concern = 4
Fairly concern = 3
Not very concern = 2
Not at all concern = 1

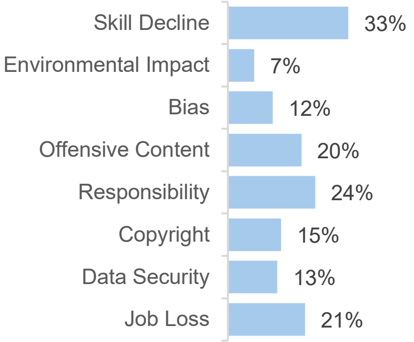
Perceived benefits by attribute



			AVG.
Learning & Skills	32%	↓	51%
Efficiency	27%	↓	55%
Creativity	26%	↓	39%
Cost Saving	14%	↓	32%

Perceived concerns by attribute

* Higher mean high concern



			AVG.
Skill Decline	33%	↓	65%
Environmental Impact	7%	↓	26%
Bias	12%	↓	49%
Offensive Content	20%	↓	48%
Responsibility	24%	↓	47%
Copyright	15%	↓	44%
Data Security	13%	↓	40%
Job Loss	21%	↓	42%

Experience using LLMs (Mean)

Use regularly= 5
Used it a few times= 4
Not sure if I have used it before = 3
No I haven't, but I am open to using it= 2
No I haven't but I wouldn't want to either= 1

			AVG.
Uses LLMs for Web/Search	2.28	↓	2.58
Uses LLMs for Entertainment/Fun	1.91	↓	2.00
Uses LLMs for Learning	2.02	↓	2.22
Uses LLMs for Career Help	1.79	↓	1.87
Uses LLMs for Daily Tasks	1.98	↓	2.16
Uses LLMs for Personal Advice	1.86	↓	1.92

Persona

Margaret, a 65-year-old retired HR administrator living in the Southeast of England. She can manage basic tasks but struggles with digital video or photo editing. While she acknowledges the efficiency of LLMs, her perception remains negative due to high concern about skill decline and her personal data security. Therefore, her use of LLMs is limited to seeking answers and does not make decisions based on AI outputs. Government is essential in ensuring that developers disclose information about AI systems and in restricting the development and use of unsafe AI products.

Proficient Pragmatic Enthusiasts 23.74%

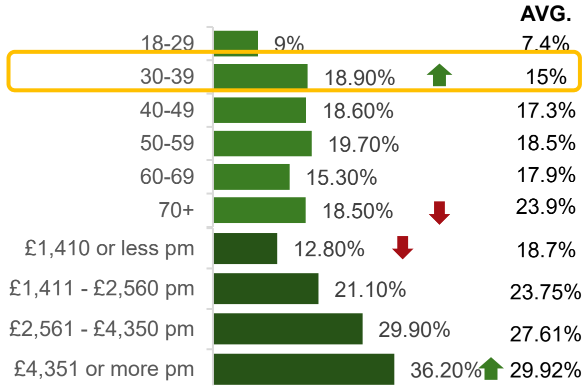
“Daily workflow: search → summarise → outline → polish. It fits right in.”

↑ Significantly higher than average at 95% confidence level

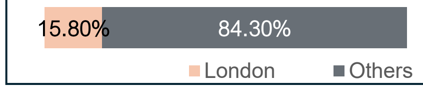
↓ Significantly lower than average at 95% confidence level

(OpenAI, 2025)

Demographic and socioeconomic status



		AVG.
Managerial & professional occupations	63.1% ↑	56%
Intermediate occupations	9.1%	10.5%
Small employers & own account workers	6.6%	6.7%
Lower supervisory & technical occupations	9%	8.8%
Semi-routine & routine occupations	8.5% ↓	12.5%
Not classifiable	3.6%	5.1%



Attitude and behaviour toward GenAI

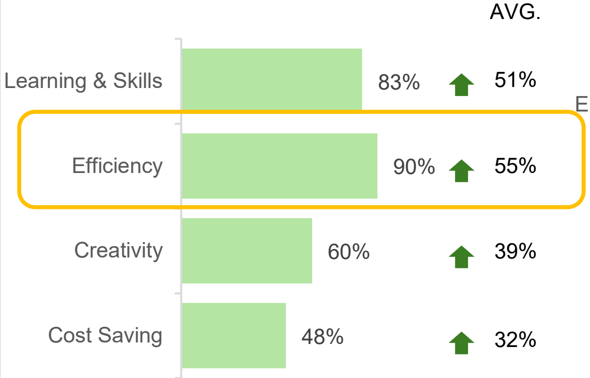
Overall Perceived benefits: Mean: 3.23 ↑ AVG 2.88

Very beneficial = 4	Not very beneficial = 2
Fairly beneficial = 3	Not at all beneficial = 1

Overall Perceived concern: Mean. 2.36 ↓ AVG 2.52

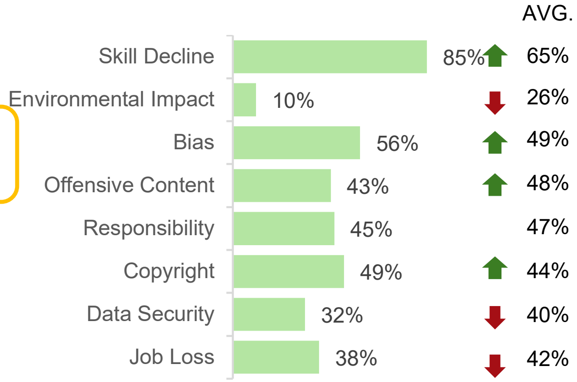
Very concern = 4	Not very concern = 2
Fairly concern = 3	Not at all concern = 1

Perceived benefits by attribute



Perceived concerns by attribute

* Higher mean high concern



Experience using LLMs (Mean)

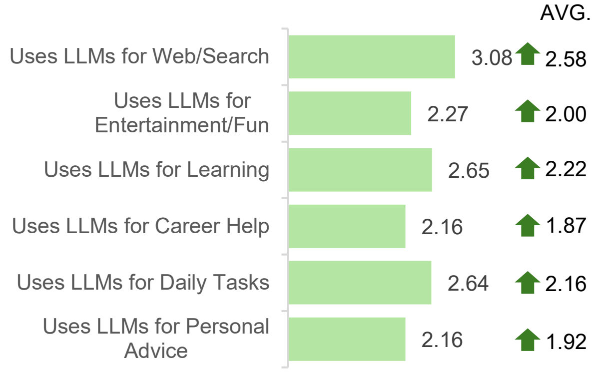
Use regularly= 5

Used it a few times= 4

Not sure if I have used it before = 3

No I haven't, but I am open to using it= 2

No I haven't but I wouldn't want to either= 1



Persona

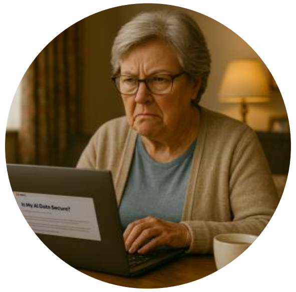
Daniel, a 44-year-old project consultant in London, represents the segment persona. Daniel is highly proficient in digital tools, from everyday tasks to intermediate-level tasks like video and image editing. He uses LLMs frequently to find answers and is open to broader applications, such as job applications and professional advice. He sees strong benefits from AI, particularly in healthcare (e.g., cancer diagnosis) and facial detection. He trusts public organisations with data sharing and is more comfortable than others with AI-supported decision-making. Although he remains cautious about the potential harm from AI content, he believes that government regulation is vital to ensuring safe and responsible AI use.

Risk-averse Sceptics 21.58%

"These tools make people lazy, and skills will decline."

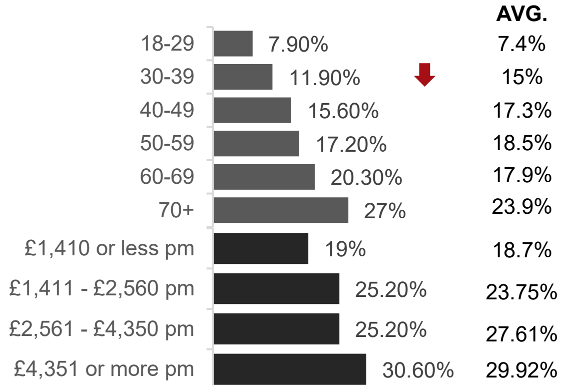
↑ Significantly higher than average at 95% confidence level

↓ Significantly lower than average at 95% confidence level



(OpenAI, 2025)

Demographic and socioeconomic status



			AVG.
18-29	7.90%		7.4%
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40-49	15.60%		17.3%
50-59	17.20%		18.5%
60-69	20.30%		17.9%
70+	27%		23.9%
£1,410 or less pm	19%		18.7%
£1,411 - £2,560 pm	25.20%		23.75%
£2,561 - £4,350 pm	25.20%		27.61%
£4,351 or more pm	30.60%		29.92%

		AVG.
Managerial & professional occupations	58.4%	56%
Intermediate occupations	9.8%	10.5%
Small employers & own account workers	6.7%	6.7%
Lower supervisory & technical occupations	8.6%	8.8%
Semi-routine & routine occupations	12.9%	12.5%
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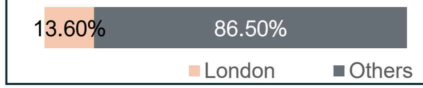


Attitude and behaviour toward GenAI

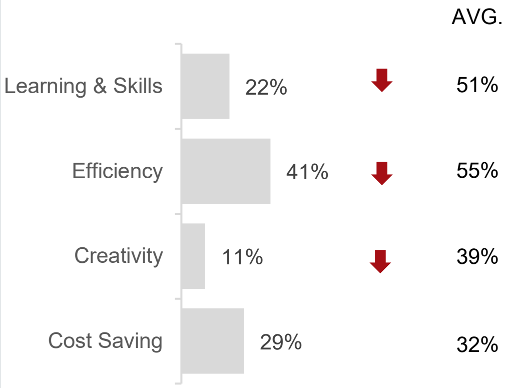
Overall Perceived benefits: Mean: 2.46 ↓ AVG 2.88

Very beneficial = 4
Not very beneficial = 2
Fairly beneficial = 3
Not at all beneficial = 1

Overall Perceived concern: Mean. 3.01 ↑ AVG 2.52

Very concern = 4
Not very concern = 2
Fairly concern = 3
Not at all concern = 1

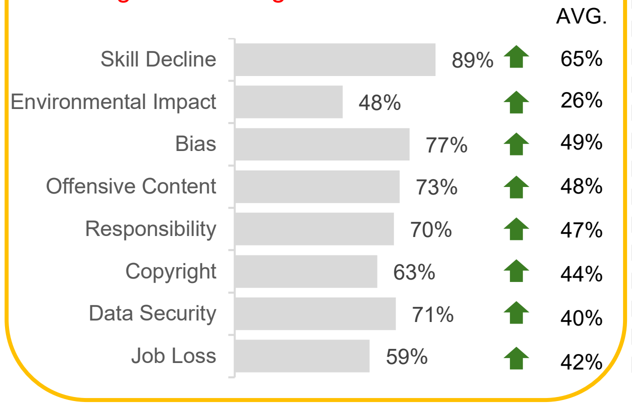
Perceived benefits by attribute



			AVG.
Learning & Skills	22%	↓	51%
Efficiency	41%	↓	55%
Creativity	11%	↓	39%
Cost Saving	29%		32%

Perceived concerns by attribute

* Higher mean high concern



			AVG.
Skill Decline	89%	↑	65%
Environmental Impact	48%	↑	26%
Bias	77%	↑	49%
Offensive Content	73%	↑	48%
Responsibility	70%	↑	47%
Copyright	63%	↑	44%
Data Security	71%	↑	40%
Job Loss	59%	↑	42%

Experience using LLMs (Mean)

Use regularly= 5
Used it a few times= 4
Not sure if I have used it before = 3
No I haven't, but I am open to using it= 2
No I haven't but I wouldn't want to either= 1

			AVG.
Uses LLMs for Web/Search	2.24	↓	2.58
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Uses LLMs for Learning	1.82	↓	2.22
Uses LLMs for Career Help	1.52	↓	1.87
Uses LLMs for Daily Tasks	1.74	↓	2.16
Uses LLMs for Personal Advice	1.64	↓	1.92

Persona

Susan, a 61-year-old retired teacher living in Yorkshire. She can use digital tools for basic purposes, such as web searches, but rarely engages in more advanced activities. When it comes to LLMs, she has heard of them and may be open to trying, but they have no significant role in her life. She recognises some benefits, such as cancer diagnosis and face detection, and has a low concern about public data sharing; yet, her limited experience makes her uncomfortable with AI in decision-making. For Susan, AI is neither a major threat nor an opportunity; it remains irrelevant unless it adds value to her routine.

The Emerging Cautious Optimists 16.82%

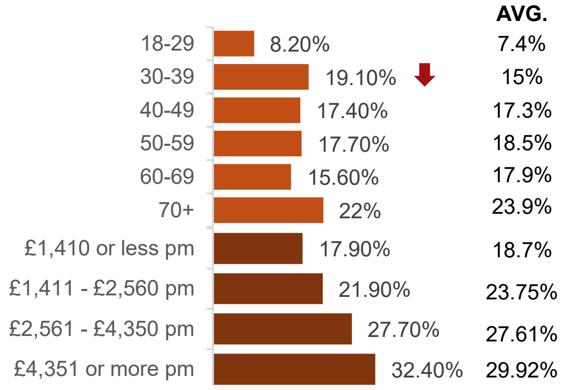
“Great for quick answers and ideas, I still double-check the sources.”

⬆ Significantly higher than average at 95% confidence level

⬇ Significantly lower than average at 95% confidence level

(OpenAI, 2025)

Demographic and socioeconomic status



	CL	AVG.
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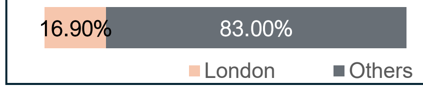
Not classifiable	3.7%	5.1%



Attitude and behaviour toward GenAI

Overall Perceived benefits: Mean: 3.15 ⬆ AVG 2.88

Very beneficial = 4
Fairly beneficial = 3
Not very beneficial = 2
Not at all beneficial = 1

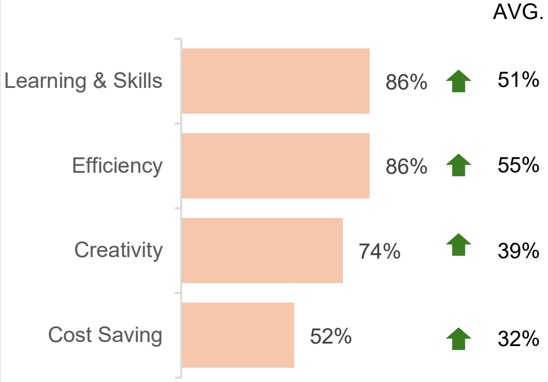
Overall Perceived concern: Mean. 2.64 ⬆ AVG 2.52

Very concern = 4
Fairly concern = 3
Not very concern = 2
Not at all concern = 1

Experience using LLMs (Mean)

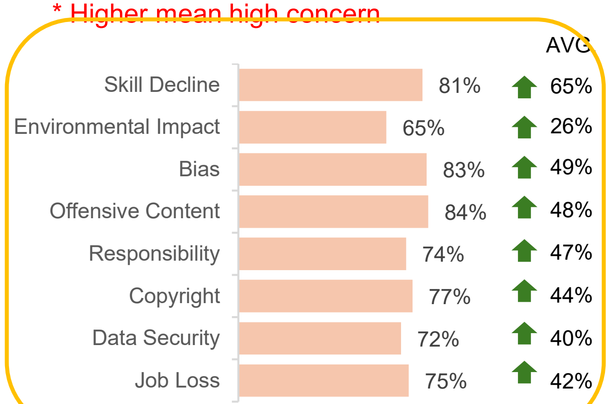
Use regularly= 5
Used it a few times= 4
Not sure if I have used it before = 3
No I haven't, but I am open to using it= 2
No I haven't but I wouldn't want to either= 1

Perceived benefits by attribute



Perceived concerns by attribute

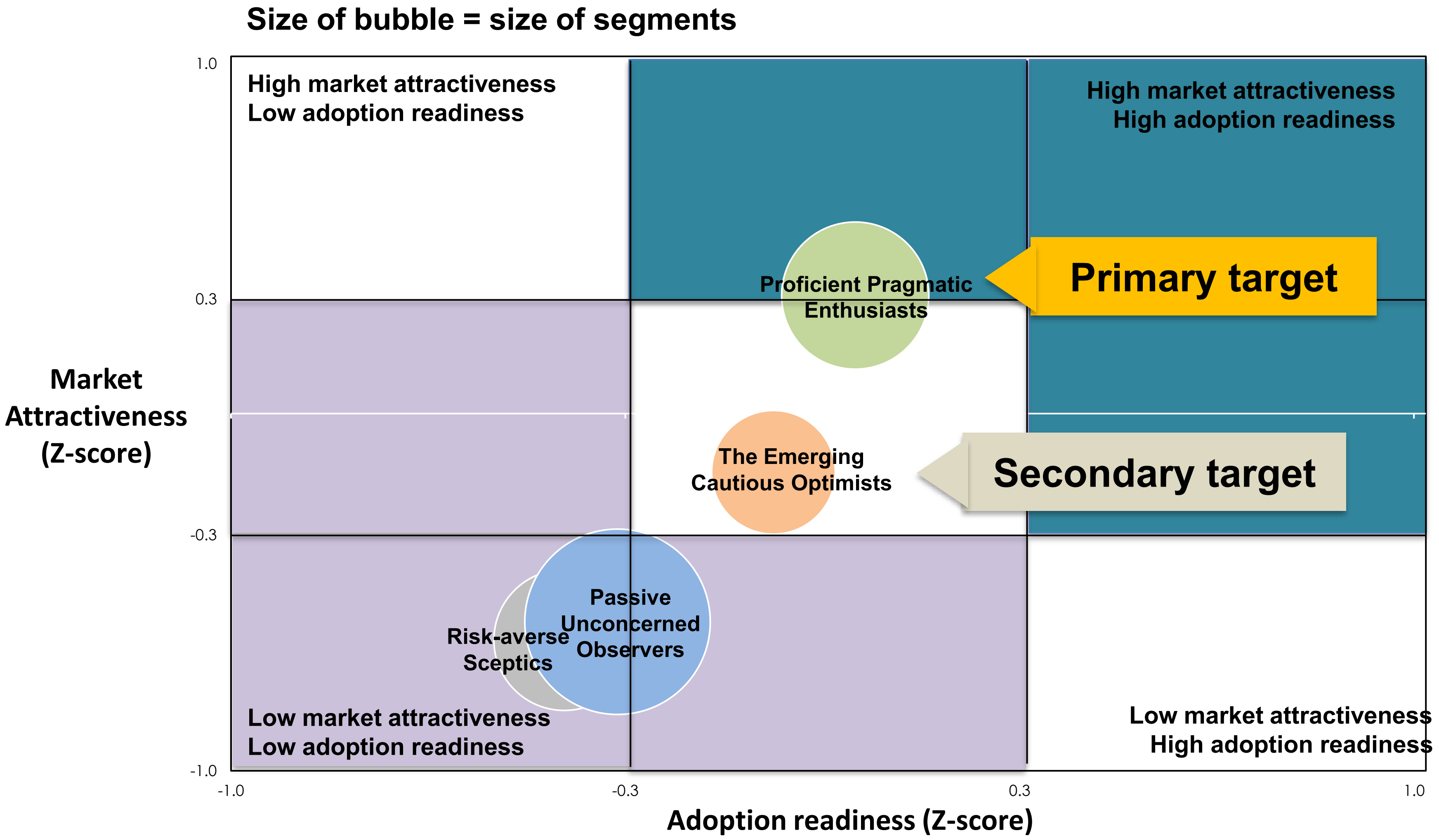
* Higher mean high concern



Persona

James, a 46-year-old project manager working and living in London with his family. He is proficient in everyday technology, such as searching and chatting, and doing intermediate tasks like verifying the source of information and solving digital problems. He rarely uses LLMs, but when he does, it is to answer simple questions, assist with education, and perform daily tasks. James sees clear benefits from AI, but remains cautious of the risks related to data privacy. For him, government regulation is important in ensuring AI safety, allowing him to remain optimistic while monitoring potential harm..

Selecting the best segment with GE Matrix



Modified GE matrix (Author's work)

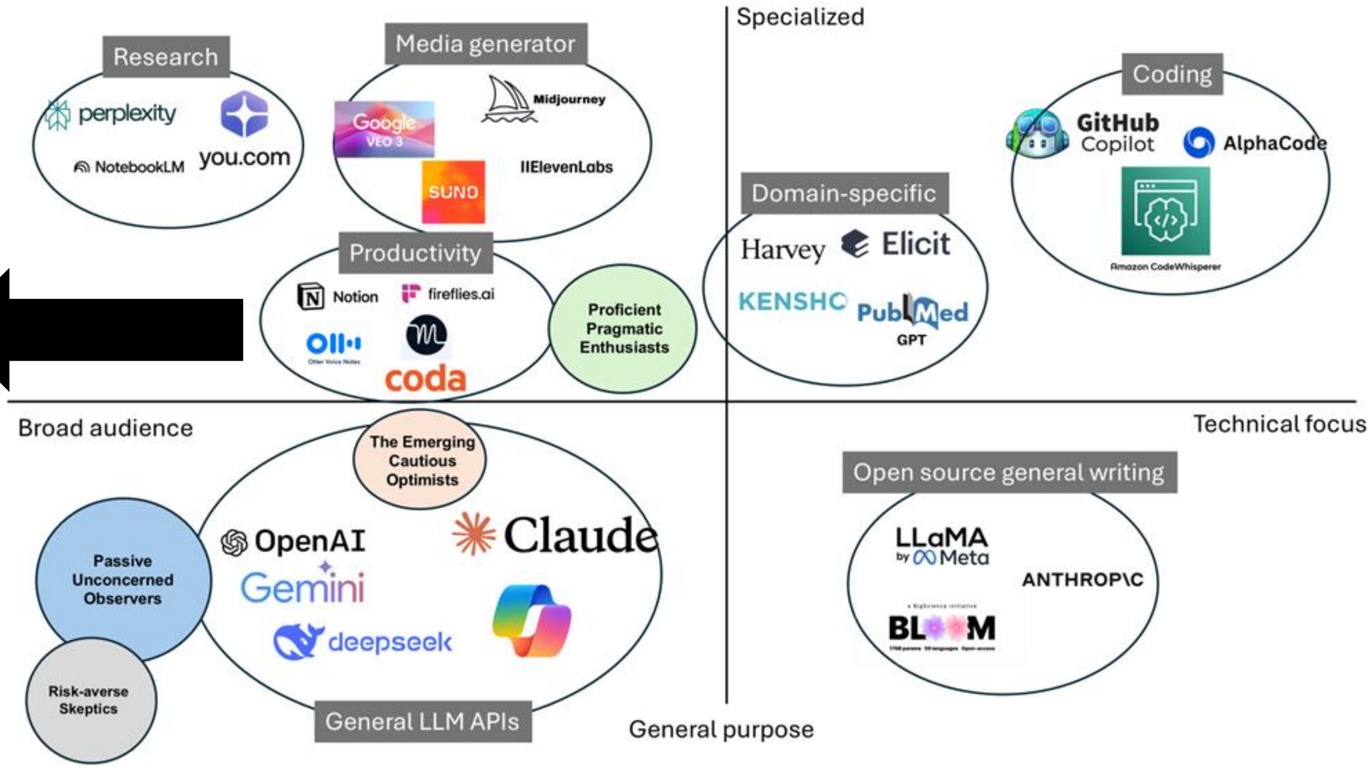
Find segment positioning with perceptual mapping and competitors analysis

- The primary target Proficient Pragmatic Enthusiasts locate near productivity and domain-specific
- The Emerging Cautious Optimists are located in general LLMs and near productivity.
- CPM is conducted to ensure that **opportunities lie in the Domain template, Transparency and safety.**

The competitor profile matrix (CPM)

Criteria	Notion AI	Firefiles.ai	Coda	
Productivity Gains	5	4	4	**13**
Workflow integration	5	4	5	**14**
Domain template	4	1	3	**8**
Transparency & Safety	4	3	3	**10**
Value for money	4	3	4	**11**
Total	**22**	**15**	**19**	

Competitor profile matrix (Author's work)



intuitive/judgmental Perceptual mapping (Author's work)

To attract targeted segments, GenAI startups should apply this communication

Proficient Pragmatic Enthusiasts 23.74%

“

(OpenAI, 2025)

For managers and specialists who want to streamline the process. The GenAI solution offers domain-specific and task efficiency. That’s because it provides an industry template, connects to existing tools, maintains data transparency, and allows control over automation levels”.

The Emerging Cautious Optimists 16.82%

(OpenAI, 2025)

“For professionals who need safe and responsible AI. This GenAI solution delivers accurate results with safeguards in place. That’s because it integrates fairness checks, content monitoring, and flexible tools for both work and personal use”.

The final tactics: Marketing mix 4Ps

4Ps template (Slide Grand, n.d.)

- Core: meeting summaries, doc drafts, explain text; audit trail
- Premium add-ons: industry templates (legal, finance); Google/Microsoft connectors
- Trust: “reasoning steps” view; data-use controls

- Free: General templates & summaries.
- Specialised (industry template): $8/user/mo (annual) or $10/mo (monthly).

- Message: efficiency + domain expertise (short before/after case)
- Transparency: open-source model, reasoning steps, training-data disclosure

- Direct SaaS: self-serve; Google/Microsoft SSOMarketplaces: Microsoft 365; Google WorkspacePartnerships: legal/finance bodies for validation.

Recommendation & Next step

“To overcome GenAI startup failures via a product–market-fit solution, the firm should build a GenAI platform to increase productivity in specific industries (e.g., legal and finance) while providing transparency of the output.”

Next step

1

(OpenAI, 2025)

Research

Conduct more research on the industry (e.g. finance & legal), such as focus group to understand the pain points and make the template more precise.

2

(OpenAI, 2025)

MVP

Build MVP (Minimum Viable Product) with core function such as notes/draft editor plus simple domain-specific templates and justify transparency.

3

(OpenAI, 2025)

Pilot launch

Run an MVP on targeted user, and test pricing tier, messaging, and quantify brand score to stenghten perceptual mapping and competitor profile matrix.

References (also in full reference)

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OVERCOMING FAILURE IN GENAI STARTUPS:

A CLUSTER ANALYSIS USING THE STP FRAMEWORK FOR MARKETING

BEMM 466 Business Project

Formative and Summative Assessment

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Assignment Cover Sheet	
Student ID	740014761
Module Code	BEMM466
Module Name	Business project
Assignment Title	Formative and Summative Assessment

Within the Business School, we support the responsible and ethical use of GenAI tools, and we seek to develop your ability to use these tools to help you study and learn. An important part of this process is being transparent about how you have used GenAI tools during the preparation of your assignments.

The below declaration is intended to guide transparency in the use of GenAI tools, and to assist you in ensuring appropriate referencing of those tools within your work.

The following GenAI tools have been used in the production of this work:

OpenAI, ChatGPT-5

☒ *I have used GenAI tools for brainstorming ideas.*

☒ *I have used GenAI tools to assist with research or gathering information.*

☒ *I have used GenAI tools to help me understand key theories and concepts.*

☒ *I have used GenAI tools to identify trends and themes as part of my data analysis.*

☒ *I have used GenAI tools to suggest a plan or structure of my assessment.*

☒ *I have used AI tools to give me feedback on a draft.*

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ABSTRACT

This dissertation-style report examines consumer heterogeneity in usage and attitude toward Generative AI (GenAI) tools to guide GenAI startups in defining the right marketing strategies to prevent failure. Several past studies on AI and GenAI have not been business-oriented and have focused on niche groups. Therefore, this study aims to apply the Segmentation-Targeting-Positioning framework (STP) to manage consumer heterogeneity. Using the secondary data source from the Ada Lovelace Institute's 2024 UK public attitudes survey (n=3,513), hierarchical cluster analysis was performed to identify meaningful segments. Targeting used modified GE matrix (Z-scores for market attractiveness and adoption readiness) to define the most promising segments. Perceptual mapping is conducted to identify the positioning of the target segment in relation to other GenAI tools on the market. Findings suggest four distinct segments: Risk-averse Sceptics (21.6%), Emerging Cautious Optimists (16.8%), Passive Unconcerned Observers (37.9%), and Proficient Pragmatic Enthusiasts (23.7%). These segments were different in terms of benefits/concerns, usage, trust, and demographics. Proficient Pragmatic Enthusiasts were selected as the primary target via GE matrix and positioning mapping. Additionally, the Competitive Profile Matrix (CPM) highlights the white space in domain-specific templates, as well as transparency/safety. The recommended 4Ps is a self-serve productivity tool with optional premium templates, featuring SaaS distribution and integration with Microsoft 365/Google Workspace. It should communicate with transparency, highlighting the source of trained data.

Keywords: generative artificial intelligence (GenAI); consumer heterogeneity; market segmentation; hierarchical cluster analysis; Segmentation–Targeting–Positioning (STP); GE matrix; perceptual mapping/positioning; Competitive Profile Matrix (CPM); product–market fit.

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1. INTRODUCTION

Over the past few years, generative AI (GenAI) tools, including ChatGPT, Gemini, Claude, and Copilot, have become a part of our daily lives. The use case ranges from daily life queries to technical support. As a result, the market is in rapid growth and is projected to reach $85 billion by 2029, with a 40% Compound Annual Growth Rate (CAGR) (Johnston, 2025). However, GenAI startups face failure rates of more than 90% due to operational challenges and a lack of market need (AI4SP, 2024; CB Insights, 2021). Moreover, startups often operate with limited resources (Adekunle et al., 2024), and the disparity in consumer demand makes it more challenging. To overcome the challenge, GenAI startups need a targeting strategy and a marketing framework that emphasises GenAI usage and attitudes to determine product-market fit.

Recent studies on GenAI segmentation are limited to a specific context. For example, Beckman et al. (2025) segment GenAI's user usage and attitudes, but the focus is on university students. At the same time, the UK national survey from the Ada Lovelace Institute (2024) and Ofcom (2024) reports descriptive insights into public attitudes toward AI and GenAI. The gap occurs as the objectives are not focused on segmentation or business-oriented outcomes.

To define market needs for businesses such as GenAI startups, I have applied the Segmenting–Targeting–Positioning (STP) framework (Palmatier & Sridhar, 2021, p. 51). Segmentation organises diverse consumers into meaningful clusters. I have employed hierarchical clustering to identify distinct segments. Then the segments are described with additional profiles to create nuance and conduct personas. For Targeting, the most attractive segment is selected based on the GE matrix, using market attractiveness and adoption readiness as criteria. While positioning will be conducted through perceptual mapping with competitors' analysis to define segment positioning, which leads to 4Ps marketing tactics.

This study utilises the secondary data from the Ada Lovelace Institute's UK public attitudes survey in 2024 (second wave). Part of the survey asked about Large Language Model (LLM), a subset of GenAI models specifically trained on large text corpora to understand and generate human-like language (OpenAI, n.d.). The survey's content covers usage, perceived benefits and concerns, governance/trust attitudes of LLMs, and has recorded the demographics of the respondents. The dataset is anonymised and publicly available with the link in reference (Ada Lovelace Institute, 2024) (complete variable lists and a preparation process in the Methodology section.

Therefore, the research questions are:

1. What distinct and actionable consumer segments exist among the UK's GenAI end-users based on their attitudes, behaviours, and concerns about GenAI?
2. Which user segment offers the most significant market potential for a generative AI productivity platform, and how should the GenAI platform be positioned to maximise adoption and differentiation?
3. How can these segmentation insights be translated into a targeted marketing strategy (including positioning and a 4Ps marketing mix) for a new GenAI startup?

These research questions will provide significant value to founders and project managers of GenAI startups. First, the project turns diverse consumer behaviour and various attitudes into actionable guidelines. The project result will highlight 1-2 potential segments, specify the GenAI features to build, and outline how to reach consumers, while pinpointing trust/ethic risks and their mitigation strategies. Practically, if the firm implements these strategies, it helps teams prioritise the roadmap and tailor messaging by acquiring those with the highest potential and reducing unnecessary spending.

The report begins with a literature review on the GenAI landscape and framework. Followed by data preparation, clustering methodology, and marketing framework application. Then, the results of the segmentation and description are presented along with implications in marketing and a conclusion.

2. LITERATURE REVIEW

The literature review provides an overview of the meaning of Generative AI (GenAI), its context, benefits, and drawbacks, aiming to offer a brief understanding of the tools. Then, the section will move to the context of GenAI startups and why they fail to provide a gap for the framework. The review will then be incorporated into the STP framework and the 4Ps strategy, concluding with a summary of the empirical study and an examination of the research gap.

2.1 Understanding GenAI: capabilities and limitations

Generative Artificial Intelligence (GenAI) refers to artificial intelligence that can generate text, images, and other forms of media through the utilisation of generative models (Sengar, 2024). GenAI responds to human requests through prompts and provides impressive outputs, such as crafting summaries in tables, rephrasing text, translating text, and merging information into a draft (OpenText, 2024). This results in productivity growth across the economy, while business sectors such as customer operations, marketing and sales, software engineering, and R&D are the most highly utilised of GenAI (McKinsey & Company, 2023).

To access GenAI, the most mainstream option is ChatGPT, which can be accessed through the official website (https://openai.com/) at no charge for the free version (OpenAI, n.d.). Paid tiers, such as the Plus and Pro versions, provide access to advanced models and features. This freemium model is standard across other leading GenAI platforms such as Gemini, Grok, and Co-Pilot.

As the market develops, more GenAI tools provide a range of different use cases, from creative to productivity, domain-specific, and coding. Synthesia is one of the early creative GenAI tools capable of generating avatars, videos, and voiceovers for virtual presenters (Synthesia, n.d.). Suno AI enables users to create high-quality, original music with just a simple prompt (Suno, n.d.). In the domain-specific space, Harvey.ai is designed to generate and analyse legal documents tailored to legal workflow (Harvey, n.d.). On the productivity side, Superhuman AI automates workflows and streamlines email management (Superhuman, n.d.).

Despite many benefits, GenAI have some limitations. First, GenAI can produce false output, which is referred to as “hallucination” (Huang et al., 2025). Hallucination can cause a significant impact if used in critical circumstances. Second, GenAI generates biased output that arises from the internal training data, raising ethical concerns and impacting business decision-making (Wei, 2025). Third, it carries environmental impact; graphics processing units (GPUs) required to operate GenAI consume a significant amount of electricity and water (Hosseini, 2025). In addition, GenAI hardware components require metals, plastic, and silicone that can harm the environment during the extraction process and create e-waste when unused.

2.2 The boom and the burst: reality of GenAI startups

The successful case of OpenAI, a small research startup founded in 2015, which has since matured into a company funded by major investors such as Microsoft (OpenAI, n.d.), inspires passion in tech startups. As a result, the number of GenAI startups is rising rapidly. Many GenAI startups have achieved success in the past few years, including Anthropic’s Claude models, Stability AI’s Stable Diffusion, Perplexity AI’s research assistant, Runway’s creative suite, and Jasper’s copywriting platform, each focusing on niche solutions.

Although the market is expected to grow, only one in ten startups is expected to survive. The study by Bethlendi et al. (2025) supports the idea that failure arises from an unjustified product idea, driven by market demand, as well as poor market positioning. The technology also makes it more complex for the sector, as only 32% of AI models transition to production, and GenAI startups specifically face significant issues with extensive compute bills and model hallucinations (Masood, 2024). In addition, organisations often prefer existing vendors over new ones, which puts pressure on startups to differentiate themselves (Johnston, 2025). Despite the complexities, both tech and AI/GenAI studies consistently conclude that pre-entry market validation is crucial. This highlights the importance of well-developed market entry strategies.

An example of a failed marketing strategy was a case study of Subtl.ai, a GenAI that aims to help companies discover internal documents by using GenAI. The primary reason for the failure was that the owner was unable to handle customers from different domains (Ganguly, 2025). This implies that Subtl.ai lacked industry understanding, specifically on customer segmentation. The failure occurred due to planning failure or overconfidence in the product, resulting in a poor product-market fit.

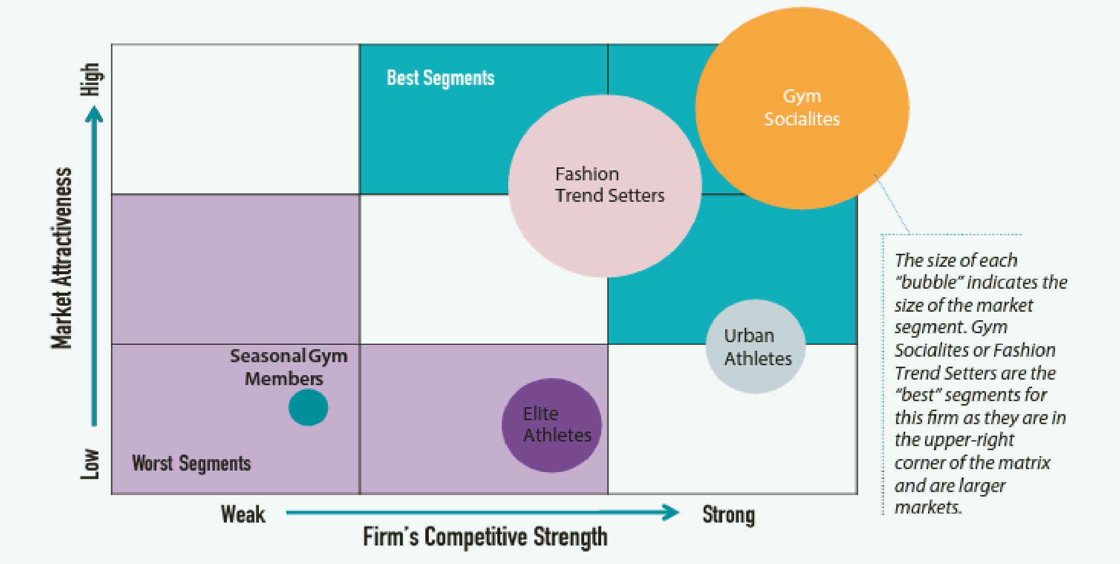
2.3 Managing consumer heterogeneity: The STP framework

To achieve product-market fit and understand consumer differences, GenAI startups must adopt a suitable market research framework that accurately reflects market needs. One of the frameworks that effectively manages consumer heterogeneity well is the

Segmenting, Targeting, and Positioning (STP) framework (Palmatier & Sridhar, 2021, p. 51). In the stage of segmentation, cluster analysis is used to classify heterogeneous consumers into a small number, then describe them by using descriptor variables. To measure heterogeneity and homogeneity, famous distances such as Euclidean (Migliore & Rossi-Lamastra, 2023) are used to group numerical or continuous data, with smaller distances reflecting high similarity (Shapcott, 2024). While measuring mixed types of variables (e.g., binary, categorical, and numerical), Gower distance can measure such data combinations by calculating the distance between each variable, which is normalised between 0 and 1, with the additional advantage of handling missing values (D'Orazio, 2021). Choosing between clustering methods is crucial; the most well-known clustering methods are K-means and hierarchical clustering. According to Kaushik & Mathur (2014), K-means is a partitioning method that organises datasets into k mutually exclusive, flat clusters. The algorithm calculates the distance between data points and cluster centroids. As a result, it works best with numerical data. In contrast, hierarchical clustering is a tree-like cluster (dendrogram). The algorithm finds the closest pair of clusters, merges them into a single cluster, and then recalculates the distances among old and new clusters. Therefore, it works well with categorical data.

Once a meaningful segment has been identified, the next step is to target the most promising subset within that segment. The GE matrix (Figure 1) can help GenAI startups focus on groups of customers that are more similar to their own capacities by plotting firm competitive strength against market attractiveness, with corresponding segments identified within (Palmatier & Sridhar, 2021, p. 56).

Figure 1: GE Matrix (Palmatier & Sridhar, 2021. P.56)

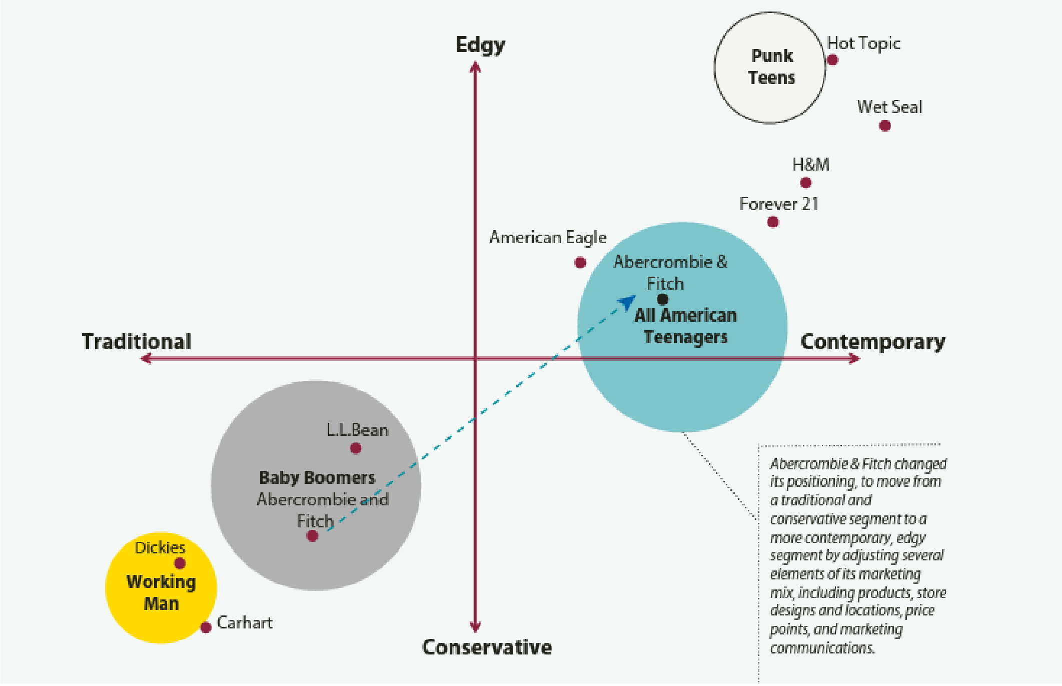


The size of each "bubble" indicates the size of the market segment. Gym Socialites or Fashion Trend Setters are the "best" segments for this firm as they are in the upper-right corner of the matrix and are larger markets.

Furthermore, BCG also developed a similar framework called the “Growth Share Matrix” (Appendix Figure A1), which classifies targets into four quadrants based on growth and share (BCG, n.d.). These matrices enable firms to manage their portfolios based on competitiveness. However, in reality, how can these segments be reached in this digital economy? The advances in big data and predictive analytics allow firms to track consumer behaviour using real-time targeting from mobile device location-based services (Camilleri, 2018). AI/GenAI startups could utilise big data such as internet usage patterns, historical searches, and locations to improve product relevancy.

The final step in STP is Positioning, a process that aligns both tangible and intangible elements with segment preferences to deliver a value proposition, utilising tools such as perceptual mapping (Figure 2). A perceptual map measures how consumers conceptually position products, based on key attributes (Kardes, Cronley, & Cline, 2011), is needs techniques such as component analysis, (multiple) correspondence analysis, and multidimensional scaling to visualise the relationship between two or more attributes (Gower et al., 2010). On the other hand, if the consumer data is absent, the firm is relying on a judgmental/ Intuitive perceptual map, but the accuracy is questionable, as it is based on a manager's judgment (Dovetail Editorial Team, n.d.)

Figure 2: Perceptual mapping (Palmatier & Sridhar, 2021, p.61)



Abercrombie & Fitch changed its positioning, to move from a traditional and conservative segment to a more contemporary, edgy segment by adjusting several elements of its marketing mix, including products, store designs and locations, price points, and marketing communications.

Finally, a positioning statement is developed to communicate and capture the target segment (Palmatier & Sridhar, 2021, p. 61). Such a statement should outline the target audience, the competitive frame of reference, the brand's point of difference, and credible reasons to believe the brand’s claims (Janiszewska, 2012). Effective product positioning must be built around benefits, differentiate from competitors, possess relevant skills, and be defensible (Camilleri, 2018). In contrast, a challenge that may arise when adopting the positioning framework for Gen AI is an ethical concern, as trust directly relates to brand perception. Zlateva et al. (2024) proposed a four-layer ethical framework that includes foundational principles (e.g., fairness, transparency), process-oriented governance across the AI lifecycle, stakeholder engagement, and contextual adaptability. GenAI startups can better align their positions to be ethically aligned with the regulation by incorporating the four-layer ethical framework.

2.4 Designing a Go-to-Market Strategy for GenAI Startups

Go-to-market (GTM) strategies are a detailed plan outlining how startups will effectively and efficiently reach their target audience (Cote, 2023). A marketing plan is necessary to implement GTM strategies by determining the sales approach to influence consumer behaviour. A foundational marketing mix framework, 4Ps, consisting of product, price, place, and promotion (McCarthy, 1964), is considered a tactical lever that leads to actionable recommendations. However, in this digital era, the traditional 4Ps may not be effective in the same way; Moore (1991) suggests the D-Day strategy for startups to focus on niche segments, such as early adopters, first by using beta as a marketing tool to gather feedback and expand more broadly during a full launch. In addition, technology enables firms to enhance the execution of their GTM strategy. Donthireddy (2024) argues that traditional GTM strategies are insufficient. Data-driven strategies, such as real-time data and predictive analytics, are needed to respond to customers promptly. In addition, NLP and CRM could perform personalised marketing that improves customer acquisition and retention rates.

2.5 Summary of empirical literature

Empirical literature on the segmentation of GenAI and Public attitudes toward AI & GenAI was summarised to identify research gaps.

2.5.1 Segmentation in GenAI

A study from Beckman et al. (2025) conducted a cluster analysis on higher education to capture student perspectives and understand the role of GenAI on students.

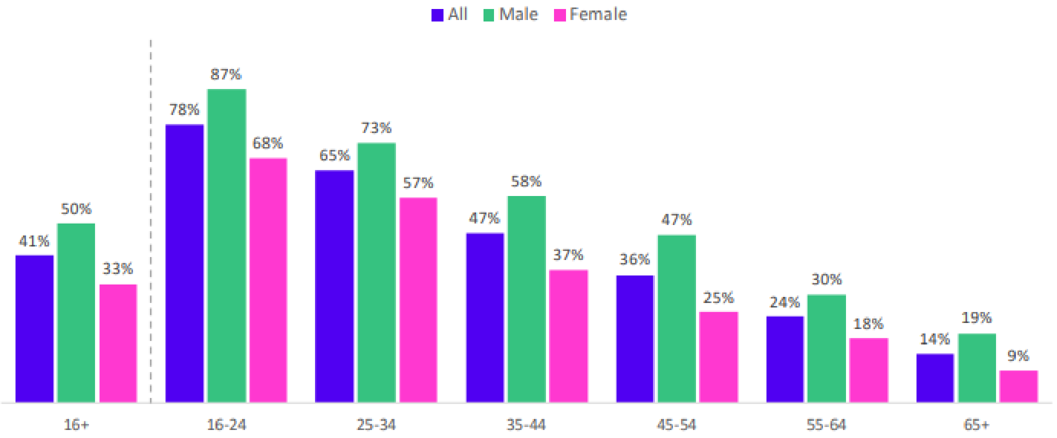
The outcomes of the segment are Novice users, Cautious users, and Enthusiastic users. Other research was also conducted on higher education, combining cluster analysis and partial least-squares structural equation modelling (PLS-SEM) to identify distinct user groups based on attitudes toward GenAI in education in Hungary (Koteczki & Balassa, 2025). The results are divided into four segments: AI sceptics, moderately open users, positive acceptors, and AI innovators. Both studies, by Beckman et al. (2025) and Koteczki & Balassa (2025), range from those who are distrustful of AI to those who are open and committed to using AI.

2.5.2 Public attitudes & trust in AI (UK Evidence)

The survey from Ada Lovelace (2024), “How do people feel about AI?”. Indicate that 61% percent have heard about LLMs, which is significantly lower compared to 90% of the awareness of AI facial recognition. For LLM usage, the trend is increasing, with the purpose of generating ideas and for everyday life queries, such as searching for answers and simple writing. Specialised tasks, such as legal/tax guidance and job applications, remain low. Beyond usage, several concerns were raised, as 66% of respondents worried that LLMs could erode problem-solving and critical thinking skills, followed by fairness and offensive content, about 47 - 48%. Digital skills and socioeconomic status influence usage; individuals with lower digital skills and lower incomes are more likely to reject using LLMs (e.g., among those unwilling to use LLMs for job applications, 27% lack basic digital skills and 39% have low incomes).

Additionally, a survey from Ofcom’s Online Nation 2024 states that young adults aged 16-24 are the group that uses GenAI the most, at 78%. When becoming older, the usage incidence declines to 14% at 65+ years old (Figure 3).

Figure 3: UK internet users aged 16+ who have used a generative AI tool in the past year, by age and gender (Ofcom, 2024)



The usage is higher among males in all age categories. Among those who are not using GenAI, the primary reasons are not interested in using it (38%) and do not need to use it (35%). Trust and concern were placed in the last two, ranked at 21% and 15% respectively. Regarding brand popularity, ChatGPT is the most widely used GenAI tool, at 33%, followed by Microsoft Copilot (15%) and Gemini (10%) in the UK. One point to note when comparing research: Because the population/age bases and measurement modes (self-report vs. self-report + passive metering) of Ada Lovelace Institute and Ofcom survey differ, percentages are not strictly comparable and recommended to observe the trend only.

2.5.3 Research gap

Prior empirical work on GenAI adoption shows methodological limitations. First, many studies use niche samples—for example, focusing on higher education or a single country only. These samples offer valuable insights, but they are not business-oriented, which is essential for GenAI startups. Second, most research on GenAI is descriptive in nature. Extensive public-attitude surveys (e.g., the Ada Lovelace Institute's reports) typically report aggregate statistics (e.g., overall percentages of perceived benefits). Although this information is valuable, it is challenging for businesses to utilise it effectively in developing targeted strategies. Therefore, a clear research gap has emerged: there is no empirical study that clusters GenAI end-users in the UK based on their needs and attitudes, and then links those segments to marketing strategies.

2.6 Key takeaway: Literature review

Although the GenAI market is growing, the startup failure rate is high due to poor product-market fits. Prior studies about AI are descriptive and not business-applicable. The STP framework can solve the issue by turning user differences into clear targets, positioning, and a practical marketing mix.

3. METHODOLOGY

To answer the first research question, What distinct and actionable consumer segments exist among the UK's GenAI end-users based on their attitudes, behaviours, and concerns about GenAI?. I have applied quantitative research, cluster analysis, using R as a data processing tool. The data is secondary, obtained from Ada Lovelace Institute's 2024 UK national survey on attitudes toward AI. Clustering is suitable because it organises data into groups based on patterns and similarity. (Yin et al., 2024).

For the second research question, "Which user segment offers the most significant market potential for a generative AI productivity platform, and how should the GenAI platform be positioned to maximise adoption and differentiation?", I have applied a modified GE matrix to target the right segment.

For the third research question, "How can these segmentation insights be translated into a targeted marketing strategy (including positioning and a 4Ps marketing mix) for a new GenAI startup?", perceptual mapping is applied to compare the targeted segment with GenAI tools in the market.

3.1 Data source

The data for cluster analysis will use secondary data from the "How do people feel about AI?" survey project. This research was led by the Ada Lovelace institute (Ada Lovelace institute, 2024), a research institute focused on data and AI for society, in partnership with The Alan Turing Institute. The data is from the second wave of the survey, which was conducted in November 2024 with 3,513 respondents.

The methodology of the survey is conducted through The NatCen Opinion Panel, which sources its participants from the highly regarded British Social Attitudes Survey (BSA) and the Life in Northern Ireland survey (LNI). A mixed-method approach was applied for data collection through the majority of online surveys, and a smaller portion was conducted by phone. The sampling design was constructed to ensure a balance of respondents' profiles. In addition, the sample included a booster of specific demographics, such as those with low digital literacy, low financial literacy, and certain ethnic backgrounds. To guarantee the accuracy of the results, statistical weighting was applied at the recruitment, sampling, and survey stages. The Link indicates OneDrive, including the R code, data & code book file, significant testing results are below.

Varis_BEMM466 shared

3.2 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is a crucial step in research, to examine the data distribution, detect outliers, and identify anomalies that inform hypothesis testing (Komorowski et al., 2016). In this study, EDA was performed on the Ada Lovelace Institute's 2024 survey dataset (n = 3,513) to prepare for hierarchical clustering. The library to conduct EDA is R's tidyverse packages for data import, tidying, manipulation, and visualisation (Wickham et al., 2019).

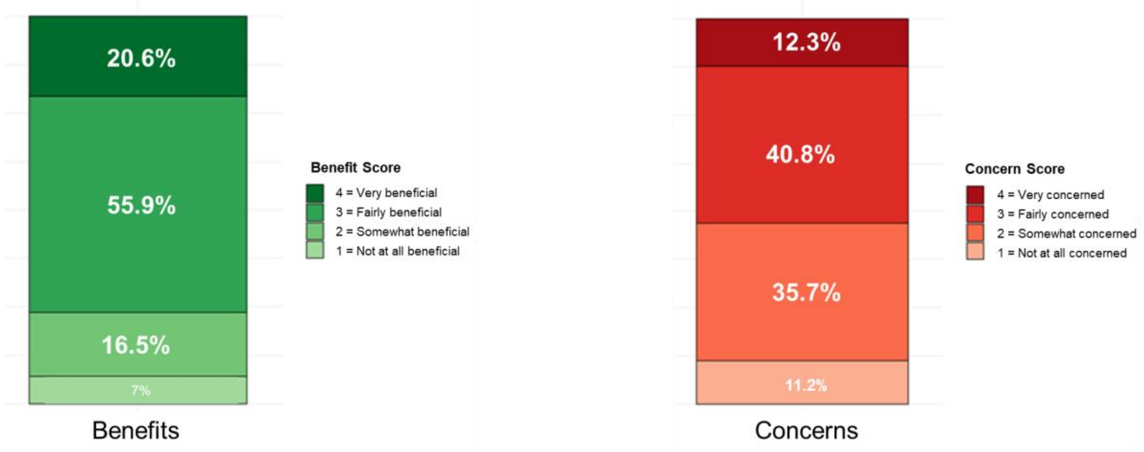
3.2.1 Data structure and understanding

The data set contains 3,513 rows and 342 variable columns, including binary variables such as BenLLMWhich1-4 (perceived LLMs benefits), ordinal variables such as ExpLLM_SearchTool_q (LLMs usage frequency), and categorical variables such as Cur_AgeCat (age groups), as defined in Dataset Codebook.xlsx.

3.2.2 Descriptive statistics

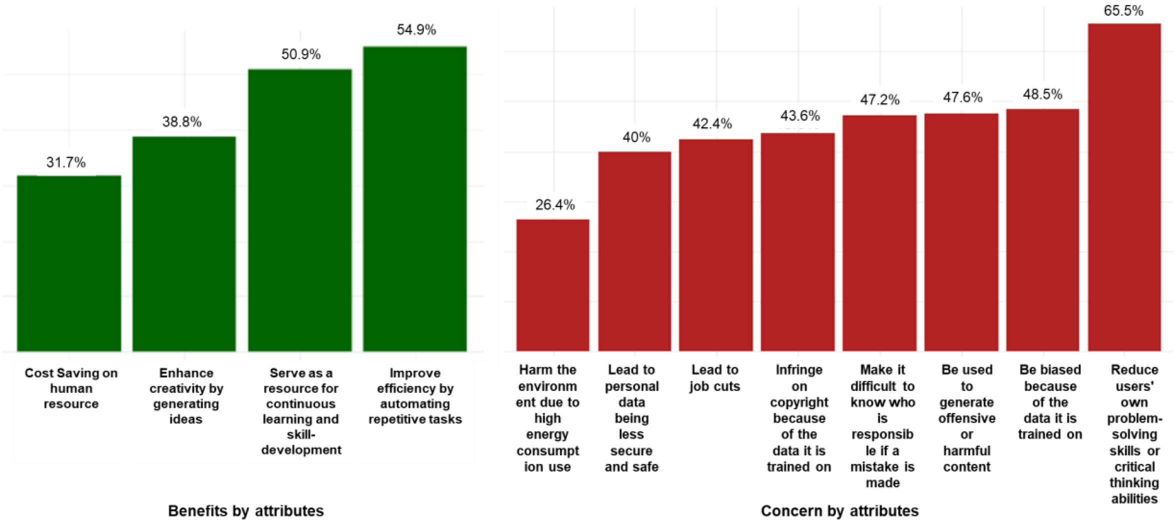
Descriptive statistics were initiated with a bar chart to visualise the distribution of cluster variable data. Figure 4 shows the distribution of LLMs' benefits (BenLLM) and concerns (ConLLM). Overall, respondents viewed LLMs as more beneficial than concerning, with the top box and top 2 boxes rating ("very beneficial" and "fairly beneficial") significantly higher than the concern.

Figure 4: LLMs Benefits (BenLLM) and Concerns (ConLLM) Rating (author's own work generated by R)



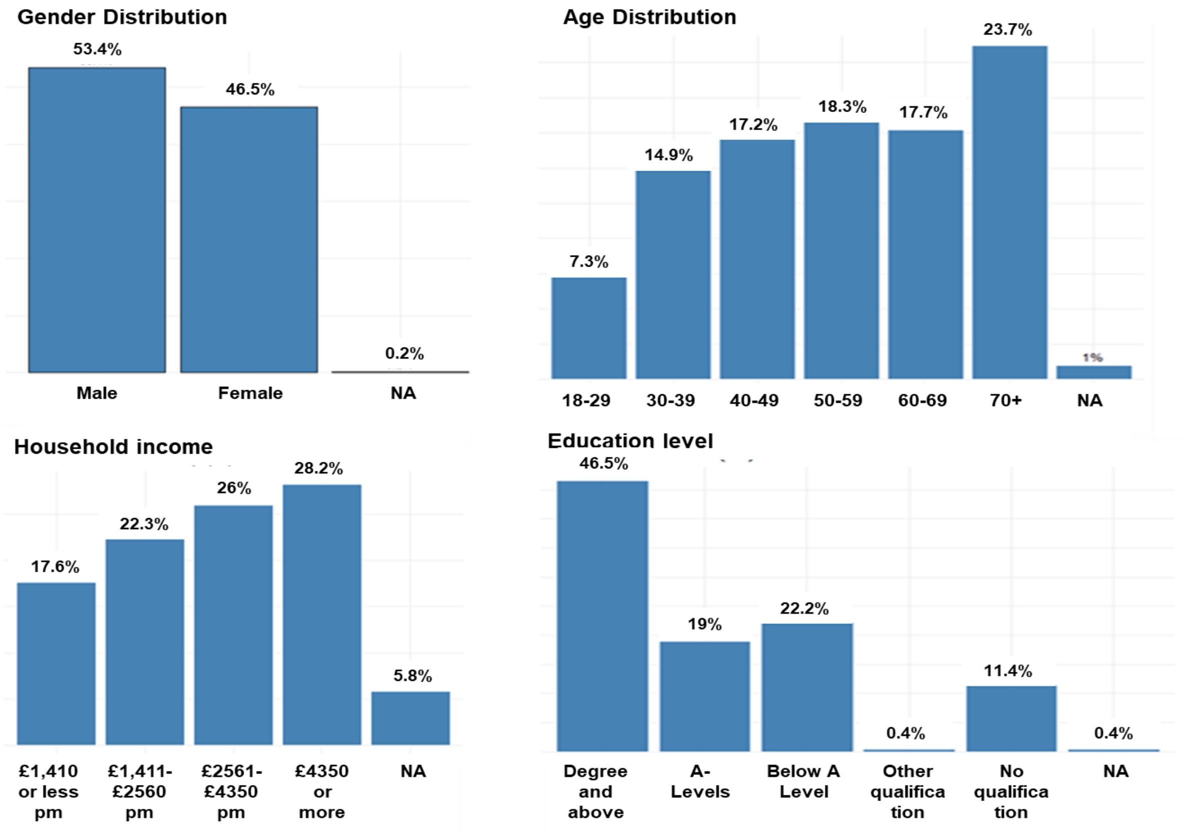
For attribute-level perceived benefits and concerns, respondents mostly report the main benefit as efficiency in handling repetitive tasks, followed by skill development (Figure 5). In contrast, skill development was also identified as the leading concern, mentioned by 65% of respondents, while energy use was the least cited concern.

Figure 5: Attribute-level perceived benefits (BenLLMWhich) and Attribute-level perceived Concern (ConLLMWhich) (author's own work, generated in R)



Demographically, the gender skew is toward females at 53.4%, compared with 51.1% in the UK population (ONS, 2023), shown in Figure 6. Age distribution heavily favours respondents aged 70+ years, compared with only 18% nationally. Education is also higher, with about half of respondents holding a bachelor's degree or above, versus the national rate at 34%. While there is no exact comparable range for household income, the survey data show 28.5% of respondents report incomes ≥ £4,351 per month (≈ £52,212 per year). Compared with ONS 2023/24 data (ONS, 2024) this threshold falls between the 70th and 80th percentiles (above £48,358, below £56,456). Therefore, the survey's income represents a slight bias toward higher-income respondents.

Figure 6: Demographic (author's own work, generated in R)



3.3 Pre-clustering process

Prior to cluster analysis, behavioural and attitudinal variables related to Large Language Models (LLMs) were selected from the Ada Lovelace Institute questionnaire, specified from the following questions:

1. To what extent do you think that the use of Large Language Models (LLMs) will be beneficial? **(BenLLM)**
2. Which of the following, if any, are ways that you think the use of Large Language Models (LLMs) will be beneficial? **(BenLLMWhich)**
3. To what extent are you concerned about the use of Large Language Models (LLMs) **(ConLLM)**
4. Which of the following, if any, are concerns that you have about the use of Large Language Models (LLMs)? **(ConLLMWhich)**

“Perceived benefits (BenLLM) were measured on a 4-point scale from ‘not at all beneficial (Scale 4)’ to ‘very beneficial (Scale 1),’ alongside a specific benefit category (BenLLMWhich). Perceived concerns (ConLLM) were captured on a parallel 4-point scale from ‘not at all concerned (Scale 4)’ to ‘Very concerned (Scale 1)’, with follow-up items identifying types of concerns (ConLLMWhich). The complete list of BenLLMWhich and ConLLMWhich is shown in Table 3. Using Psychographic or attitudinal as a cluster variable provides more homogeneous and meaningful segments than demographic-only approaches (Boslaugh et al.,2004)

Then, to ensure a valid mean calculation for clustering analysis, negative codes (e.g., -11, -9, -8 to NA) representing “do not know” or “refuse to respond”, along with codes indicating uncertainty, such as code 5 in governance variables, were removed from the calculation.

Rescaling was applied to BenLLM and ConLLM so that 1 represents “Not at all beneficial” and “Not at all concerned”, while code 4 represents “Very beneficial” and “Very concerned”. The same rescaling logic was applied to all relevant variables to ensure consistent and meaningful interpretation.

3.4 Clustering procedure

Given that the cluster variables contain both binary and ordinal scales, Gower distance is applied as the appropriate distance measurement in this mixed type of data (D’Orazio, 2021), which is defined as:

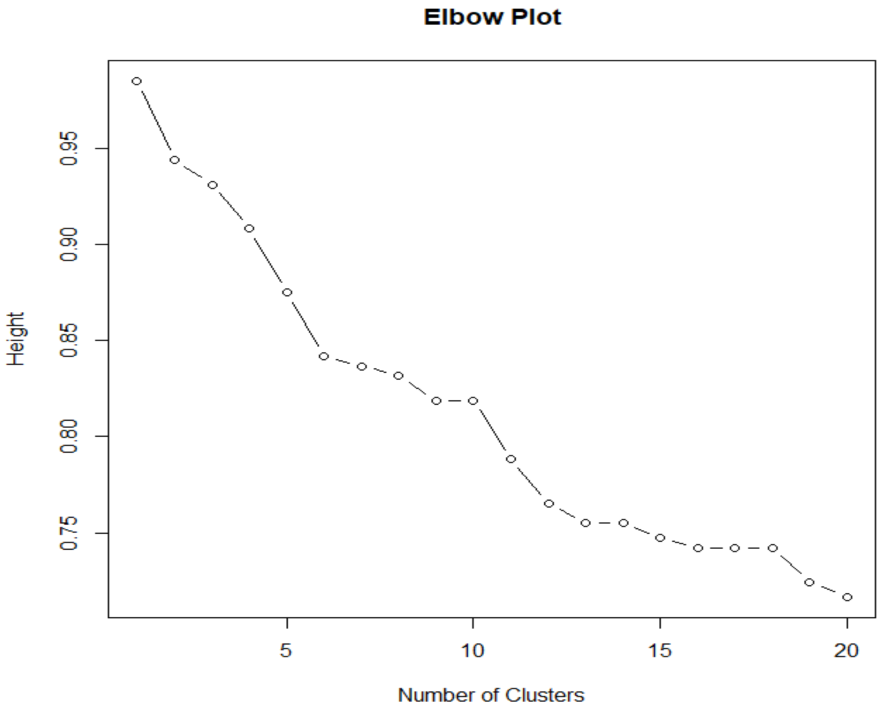
$$d_{G,ij} = 1 - s_{G,ij} = \frac{\sum_{t=1}^{p} \delta_{ijt}\, d_{ijt}}{\sum_{t=1}^{p} \delta_{ijt}} \tag{1}$$

For each variable *t*, the partial distance is defined as $d_{\{ijt\}}$ = 1 - $s_{\{ijt\}}$, where $s_{\{ijt\}}$ The similarity of *i* and *j* on variable *t* is defined according to variable types. The dissimilarity matrix was computed using the daisy() function to compute pairwise dissimilarities (distances) between observations in the data set (Maechler et al., 2025), from the cluster package in R, with weights set to 1 (default).

Hierarchical clustering with complete linkage was then performed on the Gower distance matrix. Complete linkage was chosen because the Gower distance product non-Euclidean dissimilarity matrix, so the standard Ward method is not appropriate. The hierarchical cluster result is shown in Appendix Figure A2.

To determine the optimal number of segments, elbow methods were used to suggest the numbers (Figure 7). The elbow plot suggests five clusters because the slope changes dramatically at five, but the final number will be based on cluster validation and interpretability, which is concluded in Results section 4.

Figure 7: Elbow plot (author's own work, generated in R)



3.5 Cluster & statistical validation

To validate the cluster result, the silhouette method was applied. Silhouette method evaluates its tightness and separation by showing which objects lie well within the cluster (Rousseeuw, 1987), with the score closer to 1 indicating "well clustered." Table A1 in the appendix represents the average silhouette ranging from 2 to 8 clusters. The 4-cluster solutions scored the highest at 0.153. Although this value is low and near zero, indicating poor clustering, low silhouettes are familiar in mixed datasets with nominal/ordinal variables (Coombes et al, 2021). For this reason, I will interpret silhouettes cautiously and focus on meaningful segments and application.

Beyond silhouette validation, I considered whether clusters are interpretable and actionable. A valid segment is one I can name clearly and distinctively. I have shown how each segment was named in section 4 (Result).

To test the statistical difference among clusters, one-way ANOVA is used for scale data (e.g., BenLLM_Score, ConLLM_Score, experience scales), where the F test was significant at (α=0.05). Then, Tukey HSD post hoc is applied to the identified pairwise differences. Binary and categorical variables (benefit/concern items, demographics) were analysed using Pearson's Chi-square (χ^2); pairwise proportion tests were conducted following significant results. The full result of significant testing is shown in Onedrive link **Varis BEMM466 shared** label "Significant test result", with the use of ChatGPT 5 to conduct a full code. The prompts are recorded in Appendix B labelled "Significant test result".

3.6 Targeting method

Once clusters are defined and described, the GE matrix is applied to develop a targeting strategy. According to Palmatier & Sridhar (2021, p. 56), the Y axis in the GE matrix represents market attractiveness. The X-axis initially represents firm competitiveness, but I adapted it to Adoption readiness for the suitability of the Startup context, which remains uncertain about their firm competitiveness. Variables mapped to each axis, as shown in Table 1, quantify market attractiveness and adoption readiness for precise segment positioning.

Table 1: Variable mapped to GE axes (author's own work)

	Positive variables	Negative variables
Market attractiveness	• Overall benefit of LLMs, • Benefits of LLMs by attribute, • Income, and • AI benefits	• Overall concern about LLMs, • Concern of LLMs by attribute, and • frequency of seeing AI-harmful content
Adoption readiness	• Experience using LLMs, • Comfort with AI making decisions, and • Digital skills,	• Concern about data sharing with AI • Overall concern about AI harm

To equally measure the mixed type of data within the GE Matrix, standardised Z-scores are calculated using the formula (Andrade, 2021) :

$$z = \frac{x-\mu}{\sigma} \tag{2}$$

Where:
x = observed value
μ = Sample mean
σ = Sample standard deviation
Market Attractiveness = mean(Z of all positive variables) − mean(Z of all negative variables).
Adoption Readiness = mean(Z of all *positive* variables) − mean(Z of all *negative* variables).

This method is particularly suitable for the dataset, as it comprises binary, categorical, and ordinal scales. Then, a composite net score is calculated by averaging the positive Z-scores and offsetting them by the average negative Z-score to capture the net score. Clusters were then plotted in the modified GE Matrix, with bubble size representing segment share. Segments that lie within the top right area indicate a strong target, while segments that lie in the bottom left area indicate a low targeting opportunity.

3.7 Positioning method

Following the segment targeted, I applied **perceptual mapping** to benchmark against competitors in the GenAI market. The X axis represents the scope of problems solved (generalist vs specialist) while the Y axis represents the product's user orientation (general to specialised). These X and Y axes are selected because they align with factors influencing GenAI use intention, which are perceived usefulness and perceived ease of use (Kim, 2025). The Other GenAI platforms are categorised by use case and positioning along with the segments into the following groups: General LLMs, Open-source for general writing, Research, Productivity, Media generator, Domain-specific, and Coding. This categorisation allows me to align and position the usage experience of LLMs (Appendix Table A3) with other GenAI platforms.

In the absence of consumer data, I need to adopt a judgmental/ Intuitive perceptual map. I am aware this method may introduce some bias that arises from subjective positioning. I will verify the assessment with a qualitative rubric via the insight from official websites, user reviews, and personal experience.

3.8 Competitor analysis

After perceptual mapping, competitor analysis was conducted on the area of competitors that are positioned near our targeted segment. I applied the Competitive Profile Matrix (CPM), which is a weighted matrix of key success factors (KSFs) for competitors, assigning weights based on importance and rating each GenAI tool (Sohel et al., 2014). Each brand is rated 1–5, from major weakness to strength; however, I decided on an unweighted CPM because there is a lack of importance data to justify the precise weight. To select KSFs, I have combined the attributes from BenLLMWhich and ConLLMWhich, as presented in the survey by Ada Lovelace Institute (2024), with the checklist for GenAI solutions (Reuter, 2023). The final factors to evaluate GenAI tools are Productivity Gains, Workflow integration, domain templates, transparency and safety, and Value for money. Regarding the threshold of each factor, I have derived it from the market scan. The summary of the factor, definition, and the threshold justification is shown in Table 2.

3.9 Marketing mix 4Ps

As the final strategic tactic, the marketing mix framework, comprising the 4Ps of product, price, place, and promotion, was applied (McCarthy, 1964). The outcome of 4Ps will directly link to the findings. Product features were derived from the significant perceived benefits of the targeted segment. Price was benchmarked against competitors. The place was derived from the segment profile. The promotion message was derived from perceptual mapping and the proposition statement.

Table 2: Competitors' benchmarking criteria (author’s own work)

Factor	Definition	Threshold justification
Productivity Gains	How much can tools improve efficiency, reduce workload and complete tasks	1 - Only one core AI function 2 - 2–3 AI functions 3 – 3–5 AI functions 4 – 5+ AI functions 5 – 7+ AI functions
Workflow integration	Ability to connect to other tools seamlessly	1 - No integrations or API support. 2 - Limited integrations (1–3 primary tools), no API. 3 - Moderate integrations (4–9 tools), no API 4 - Broad integrations (10+ tools or API access). 5 - Extensive integrations (10+ tools, API access, deep customisation, and automation triggers).
Domain template	Availability of ready-made templates tailored to specific industries	1 – None. 2 – Basic, general only. 3 – General + some industry. 4 – Broad industry coverage. 5 – Extensive, updated, multi-industry, adaptable.
Transparency and safety	How well the tool explains its output, manages user data, and protects against harmful and biased content	1 – No policy or safety. 2 – Basic policy, minimal safety. 3 – GDPR, opt-in AI, some moderation. 4 – GDPR, clear policy, safety settings, partial transparency. 5 – High transparency, bias reports, strong safety, and complete user control.
Value for money	Price competitiveness is based on the lowest available paid tier (per user/month), the availability of a free plan, and the percentage of core features included in the free or entry-tier plan.	1 – No free, >$30 pm, ≤7d trial 2 – No free, $21–$30 pm, ≤14d trial, 3 – Free, $11–$20 pm. 4 – Free, $6–$10 pm. 5 – Free, ≤$5 pm.

3.10 Ethical considerations

The secondary data from Ada Lovelace Institute is anonymous, as it does not contain personal information, such as name, phone number, or address. This ensures compliance with ethical standards and data protection regulations. Additionally, the NatCen Opinion Panel adheres strictly to ethical and privacy guidelines, such as asking permission and skipping to personal information, keeping the data safe according to GDPR (NatCen, n.d.). This outlined how participant data is securely managed throughout the research.

Regarding the analysis stage, the focus will shift toward algorithmic bias in the clustering process. This is because segmentation can sometimes cause unintentional overlooking of demographic or attitude. To mitigate this risk, the analysis will be carefully reviewed to ensure no bias occurs. Furthermore, the actionable marketing strategies in this study will be fair and transparent in both analysis and implementation stage.

All research activities will be conducted in full compliance with the University of Exeter's Research Ethics Framework and the specific guidance for the BEMM466 module. This includes adhering to the data protection and storage protocols, such as using the University of Exeter OneDrive for all data storage and ensuring the complete destruction of the data by the specified deadline.

In addition, AI-generated codes and images (from the executive summary) are recorded with prompts in Appendix B. I decided to use AI-generated images to represent personas to avoid the portrayal of real persons

3.11 Risks and Limitations

As this study utilises secondary data from the Ada Lovelace Institution, the dataset overrepresents older and higher-income groups compared to the UK population. This bias may influence usage patterns and attitudes toward GenAI.

Secondary data also poses a control limitation. First, the survey design is fixed, such as how the question is asked or the question format (e.g., binary or scale). This affects the distance method for cluster analysis. Second, it limits the ability to analyse because Variable availability is restricted. These limitations can be partially mitigated through careful interpretation and the use of supplementary data to strengthen the findings.

3.12 Key takeaway: Methodology

Using Ada Lovelace Institute UK’s national survey (n = 3,513), the attitude towards LLMs was cleaned and rescaled, along with EDA, to prepare the Hierarchical clustering process using Gower distance. The segment solution will then be inserted into the GE matrix for targeting and perceptual mapping to position the brand. A Competitive Profile Matrix (CPM) will be used to identify additional opportunities that translate into an actionable 4Ps plan.

4. RESULTS

The result is presented according to the STP framework, beginning with clustering results, including characteristics and personas, followed by targeting through the GE matrix, segment proposition (positioning), competitors analysis, and the 4Ps

4.1 Clustering results

Cluster analysis generated four distinct segments (Table 3). Cluster 3 dominates with 37.86% of respondents, followed by Clusters 1 and 4, while Cluster 2 is the smallest, accounting for 16.82%. I have applied conditional formatting to aid the interpretation, with green representing positive values and red representing negative values. Segment naming and description are based on core cluster variables, which are perceived benefits and concerns towards LLMs. While AI readiness, trust factors, demographic and socioeconomic status will serve as supporting information to add nuance to each profile. With the integration of these dimensions, the segment persona will be fully developed for targeting and positioning strategies.

The overall perception of LLMs is reported as a mean from four-point ordinal scale data, where scores closer to 4 indicate more substantial perceived benefits; conversely, scores closer to 4 indicate high concern. Attribute-level benefits are measured by a binary variable, with a mean closer to 1 implying a higher perceived benefit. A score closer to 1 indicates a higher level of concern.

Beyond core attitudinal variables, AI readiness and trustworthiness offer additional insights. Appendix Table A1 includes additional variables, such as the experience with LLMs, the benefits of AI, the harms of AI, the comfort of AI in decision-making, and views on government involvement, which will be used to support product and communication strategies. Digital skills levels are also presented to understand the proficiency of each group. Demographics such as age, gender, race, and socioeconomic status, including household income, household type, and occupation, will be Used to support and create nuance of each cluster, as shown in Appendix Table A2.

Table 3*: Cluster analysis results (author's own work)*

	Cluster	1	2	3	4
	Size in %	21.58%	16.82%	37.86%	23.74%
Overall perception of LLMs (mean)	Overall benefit of LLMs	2.46	3.15	2.77	3.23
	Overall concern of LLMs	3.01	2.64	2.29	2.36
Benefits of LLMs by attribute (mean)	Serve as a resource for continuous learning and **skill-development**	0.22	0.86	0.32	0.83
	Improve **efficiency** by automating repetitive tasks	0.41	0.86	0.27	0.90
	Enhance **creativity** by generating ideas	0.11	0.74	0.26	0.60
	Cost Saving on human resource	0.29	0.52	0.14	0.48
Concern of LLMs by attribute (mean)	**Reduce users' own problem-solving skills** or critical thinking abilities	0.89	0.81	0.33	0.85
	Harm the environment due to high energy consumption use	0.48	0.65	0.07	0.10
	It is **biased** because of the data it is trained on	0.77	0.83	0.12	0.56
	It is used to generate **offensive or harmful content**	0.73	0.84	0.20	0.43
	Make it difficult to know who is **responsible** if a mistake is made	0.70	0.74	0.24	0.45
	Infringes on copyright because of the data it is trained on	0.63	0.77	0.15	0.49
	This leads to **personal data being less secure** and safe	0.71	0.72	0.13	0.32
	Lead to job cuts	0.59	0.75	0.21	0.38

4.2 Segment 1 description

From a read of the colour-coded data in Table 3, Cluster 1's perception of LLMs is negative. Overall perceived benefit is the lowest at 2.46 (between 'fairly beneficial' and 'not very beneficial'), while overall concern is the highest at 3.01 (somewhat concerned). In terms of specific benefits, efficiency is the most valuable attribute for this group. However, its ratings are significantly lower than those of Clusters 2 and 4, yet higher than those of Cluster 3. Attribute-level concerns are relatively high but remain significantly lower than those in Cluster 2. Concern over skill decline is significantly highest across all clusters, followed by data security. This Cluster represents those who feel worried about LLMs, especially regarding skills decline and data security, while they may still believe it has some benefits in terms of efficiency enhancement. Therefore, this cluster is concluded as **"The Sceptic".**

According to Appendix Table 1, the digital skills in this group are moderate, with the ability to use search engines, visit websites, send messages, and comment and share information, as well as solve basic digital issues, at approximately 70%. LLMs usage is significantly low, with the mean around 1.78, indicating "no but open to use". The highest usage category is searching for answers and recommendations (mean 2.24). Perceived AI benefit is the lowest among Cluster, with cancer diagnostic and face detection being the most beneficial, but the rates are only "fairly beneficial". Concern over public organisations sharing personal data with AI is the highest among all groups. While government intervention is important to all clusters, this group is the most supportive of halting the development of unsafe AI products. They are also the least comfortable with AI being used for decision-making.

Insights from Table A2 in the appendix reveal a demographic profile skewed toward females, white British individuals who reside in the Southeast of England and London. The age distribution heavily favours the elderly, with more than 60% being over 60 years old. The average age is significantly higher than in Clusters 2 and 4. This results in retirees making up about 30%. Average monthly income is around £3,700, ranking third among the four clusters. With all these insights, I would add a suffix to this Cluster as "Risk-averse Sceptics**".**

The segment persona is represented by Margaret, a 65-year-old retired HR administrator living in the Southeast of England. She can manage basic tasks but struggles with digital video or photo editing. While she acknowledges the efficiency of LLMs, her perception remains negative due to high concern about skill decline and her personal data security. Therefore, her use of LLMs is limited to seeking answers and does not make decisions based on AI outputs. Government is essential in ensuring that developers disclose information about AI systems and in restricting the development and use of unsafe AI products.

4.3 Segment 2 description

Cluster 2 presents a mixture of red and green scores, with green indicating benefits and red indicating concern, reflecting a push-pull mindset. Overall perception of LLMs is positive at 3.15 ("fairly beneficial"), while concern is moderate at 2.64 ("somewhat concerned"). The most substantial perceived benefits are improving learning and skills, as well as enhancing efficiency, which is significantly higher than in Clusters 1 and 3. On the concern side, all scores are relatively high with bias (0.83) and offensive content (0.84) rated as the top issues, significantly above Cluster 1—this combination of optimism about LLMs and awareness of their risks. The attitude will be defined as "**The cautious optimist".**

Appendix Table A1 shows that this cluster is slightly more capable in basic digital tasks than Clusters 1 and 3, particularly in tasks such as verifying online information and solving fundamental digital problems. Most respondents never use LLMs but are open to trying them, while those who are using them engage in activities such as educational purposes and daily tasks, with the most common use being to find answers. They view AI as more beneficial in areas such as cancer diagnosis (3.58, "very beneficial"), but still show some concern over public organisations sharing personal data with AI. Comfort level with making decisions with AI is low, and the government remains crucial in monitoring the development of unsafe AI products.

For demographics, Cluster 2 is geared toward males, and its age range is younger than that of Clusters 1 and 3, with the majority falling between 30 and 59 years old. The primary race remains white British, but with a higher-than-average proportion of Asian. Most reside in London (16.9%), followed by southeast England (14.2%). Around half are in paid work in managerial & professional occupations, with an average income of around £4,350 per month, significantly higher than Cluster 3 and slightly above Cluster 1. I will name this cluster **"The Emerging Cautious Optimists".**

The segment persona is represented by James, a 46-year-old project manager working and living in London with his family. He is proficient in everyday technology, such as searching and chatting, and doing intermediate tasks like verifying the source of information and solving digital problems. He rarely uses LLMs, but when he does, it is to answer simple questions, assist with education, and perform daily tasks. James sees clear benefits from AI, but remains cautious of the risks related to data privacy. For him, government regulation is important in ensuring AI safety, allowing him to remain optimistic while monitoring potential harm.

4.4 Segment 3 description

As the largest segment, Cluster 3 appears to be the opposite of Cluster 2. According to Table 3, the Cluster has a moderate overall perception of benefits, with a mean of 2.77, while the overall concern is the lowest at 2.29. The attribute benefits align with the pattern, with a significantly lower score than clusters 2 and 4 in every aspect. The core perceived benefit of LLMs is in developing learning and skills. Concerns are low in most areas. This cluster represents those who are passive and disengaged with LLMs. The mindset is summarised as **“Passive observer”**.

Although they can perform basic digital tasks such as web searching, their proficiency in other skills is the lowest. LLMs usage is slightly higher than Cluster 1, but the average level remains at “no, but open to use it”. Perceived AI benefits are highest for face detection and cancer diagnosis, with lower ratings for other applications. Concern about public organisations sharing personal data with AI is relatively low, aligning with the least frequency of harmful AI content observed, which is quite aligned with their passive mindset.

Regarding demographics, this Cluster has the highest proportion of females at 57%, while the age is comparable to Cluster 1, which is in the early 60s. Most are white British and live across the UK. The economic status includes a high contribution of retirees (29.5%), though the majority remain in paid employment. The average monthly income is the lowest among all clusters, at around £3,500 per month. Therefore, with all the information, I will name this cluster **“Passive Unconcerned Observers”**

The segment persona is represented by Susan, a 61-year-old retired teacher living in Yorkshire. She can use digital tools for basic purposes, such as web searches, but rarely engages in more advanced activities. When it comes to LLMs, she has heard of them and may be open to trying, but they have no significant role in her life. She recognises some benefits, such as cancer diagnosis and face detection, and has a low concern about public data sharing; yet, her limited experience makes her uncomfortable with AI in decision-making. For Susan, AI is neither a major threat nor an opportunity; it remains irrelevant unless it adds value to her routine.

4.5 Segment 4 description

Cluster 4 is almost entirely green on the colour-coded table. The overall perceived benefits score is the highest, at 3.23, but is not significantly different from Cluster 2. Overall perceived concern is the second lowest, at 2.36. Attribute-level benefits are relatively high, particularly in terms of efficiency, learning, and skills development. One outstanding attribute-level concern is the reduction in problem-solving skills at 0.85, while bias, data security, and job loss are significantly lower than in Clusters 1 and 2. This profile reflects those who are highly optimistic about LLMs and perceive their core potential in efficiency, while remaining cautious about skill decline. I would initially imply this group as **“Pragmatic Enthusiasts”.**

This Cluster has the strongest digital capabilities of all groups. Nearly all members possess basic digital skills, and around 50% can edit images and videos online, well above the average of 42%. LLMs' usage is the highest across all tasks, aligning with their attitude. They also possess above-average perceptions of AI benefits across dimensions, express relatively high trust in public organisations to share data with AI, and are more comfortable with AI decision-making. While they occasionally encounter harmful AI content, they remain moderately concerned, encouraging their pragmatic attitudes.

They have the highest proportion of males, with a significantly younger age distribution, with the majority between 40 and 49 years old. The majority are white British, with the highest share of Asian at 17.3%. Most are in managerial and professional roles, living in London and the surrounding areas in the Southeast and Northwest. They report the highest income, close to £4,350 per month, and have the highest level of education. I would call this group **“Proficient Pragmatic Enthusiasts”.**

Daniel, a 44-year-old project consultant in London, represents the segment persona. Daniel is highly proficient in digital tools, from everyday tasks to intermediate-level tasks like video and image editing. He uses LLMs frequently to find answers and is open to broader applications, such as job applications and professional advice. He sees strong benefits from AI, particularly in healthcare (e.g., cancer diagnosis) and facial detection. He trusts public organisations with data sharing and is more comfortable than others with AI-supported decision-making. Although he remains cautious about the potential harm from AI content, he believes that government regulation is vital to ensuring safe and responsible AI use.

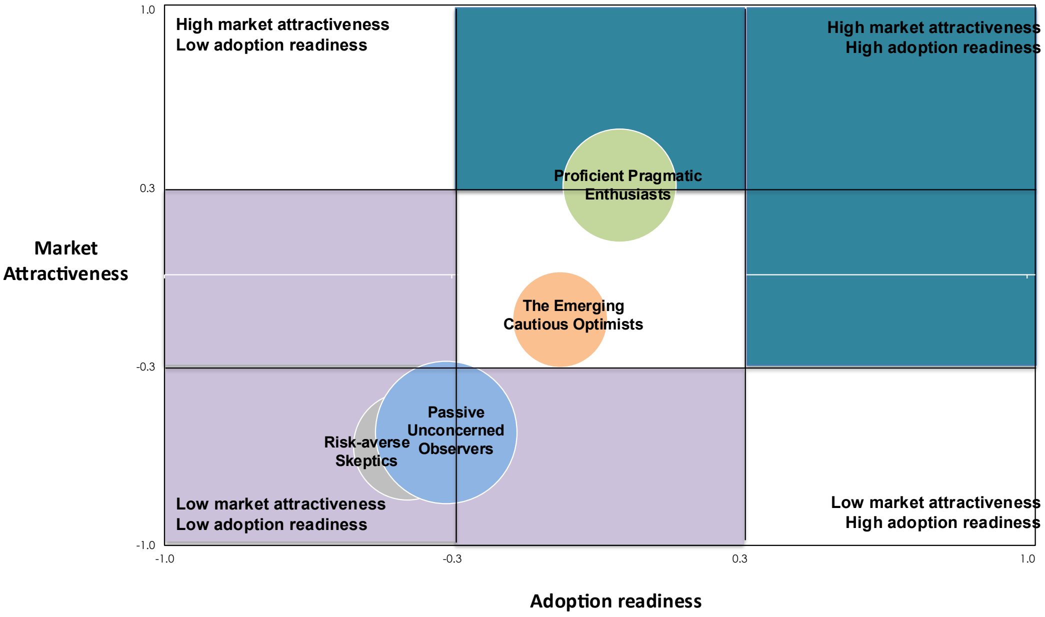
4.6 Targeting strategy

Figure 8 illustrates the segment positions, based on Z-scores, within the modified GE Matrix (Full data shown in Appendix Table A4) . The bottom-left area in purple represents a low opportunity for targeting, while the area in blue represents a high opportunity for targeting. Proficient Pragmatic Enthusiasts, with an enthusiastic positioning, is located in the blue area, which represents high market attractiveness and moderate adoption readiness. The segment is well above another cluster, implying it is a primary target.

Even though the size of Passive Unconcerned Observers is the largest, they lie entirely in the purple area alongside Risk-averse Sceptics, which indicates low market attractiveness and adoption readiness. The Emerging cautions optimists are positioned near the top right quadrant, making them the secondary target.

Figure 8*: Modified GE matrix for segmentation (author's own work)*

Size of bubble = size of segments



4.7 Perceptual mapping (positioning)

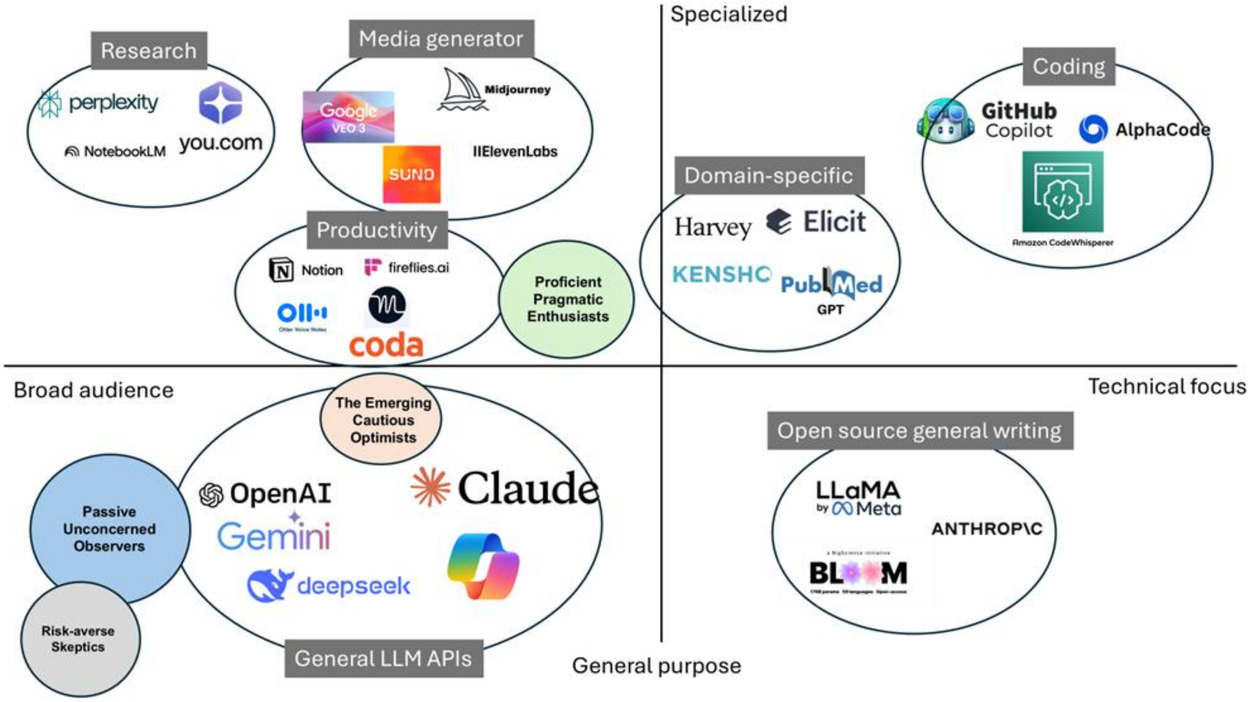
Figure 9 presents the perceptual map; Appendix Table A5 details the qualitative positioning rubric. The patterns for the two main segments are clear. Risk-averse sceptics and Passive Unconcerned Observers occupy the lower-left quadrant. The area is associated with basic GenAI, such as ChatGPT and Gemini. This is because these users show low usage and high concern with LLMs; therefore, adding any features will not change their behaviour.

In contrast, Proficient Pragmatic Enthusiasts are located in the upper quadrant, reflecting their strong perception of efficiency benefits and openness to GenAI across multiple contexts. This segment is positioned closely to productivity-focused GenAI like Notion AI and Fireflies.ai. These GenAI systems are capable of improving workflows, such as text summarisation, enhancing writing, and summarising meetings and transcripts. The segment is also located near domain-specific solutions, which are GenAI that provide knowledge to specific industries, such as medical and education. The reason behind this position is the high managerial role and income, which align with more specialised and workflow-enhanced applications.

The Emerging Cautious Optimists are positioned closer to the centre, near both general-purpose and productivity tools. This is because they remain semi-open to niche solutions but mainly use the mainstream LLMs like ChatGPT and Gemini, searching for answers and recommendations.

Figure 9: Intuitive/judgmental conceptual perceptual mapping (author’s own work)
Size of bubble = size of segments

Note. Logos reproduced from the brand-asset pages of Anthropic (n.d.), OpenAI (n.d.), Perplexity (n.d.), You.com (n.d.), … All logos are trademarks of their respective owners and used for non-commercial, academic illustrations.



Therefore, priority is placed on Proficient Pragmatic Enthusiasts as the primary target and Emerging Cautious Optimists as the secondary target for the positioning statement and go-to-market strategy in the latter part of the report. The other two segments are excluded from the strategy due to their low opportunity and general position in the mainstream GenAI.

4.8 Segment proposition

Proficient Pragmatic Enthusiasts, the segment proposition is: “For managers and specialists who want to streamline the process. The GenAI solution offers domain-specific and task efficiency. That’s because it provides an industry template, connects to existing tools, maintains data transparency, and allows control over automation levels”.

Regarding The Emerging Cautious Optimists, the segment proposition is: “For professionals who need safe and responsible AI. This GenAI solution delivers accurate results with safeguards in place. That’s because it integrates fairness checks, content monitoring, and flexible tools for both work and personal use”.

4.9 Competitor analysis (CPM)

Based on perceptual mapping, the GenAI productivity group is the closest to the primary target, Proficient Pragmatic Enthusiasts, which will be compared with. Three selected GenAI tools: Notion AI, Fireflies.ai, and Coda AI:

Notion AI is an AI workspace for notetaking, documentation, and project management. It supports summarisation, content generation, and rewriting inside collaborative pages (TaskFoundry, 2025). It integrates with Slack, Google Drive, Jira, and Figma, and supports API workflows (Notion Labs, n.d.-a). It offers a large template library adaptable to multiple industries (Notion, n.d.-d).

Coda AI is an AI-enabled document platform for building interactive docs, automating workflows, and analysing data. It supports meeting summaries, task extraction, table population, and AI-assisted formulas (Coda, n.d.-a). It integrates with Google Workspace, Slack, Jira, and external APIs through its “packs” system. It offers business-oriented templates for project tracking, marketing, and CRM databases (Coda, n.d. -c).

Fireflies.ai is an AI meeting assistant for recording, transcribing, and analysing voice conversations on Zoom, Microsoft Teams, and Google Meet. It generates searchable transcripts, meeting summaries, and action items (Fireflies.ai, n.d.-c). It integrates with CRMs like HubSpot and Salesforce, as well as project tools like Asana, to streamline post-meeting workflows (Fireflies.ai, n.d.-c). The result of the competitors' analysis is shown in Table 4. For the score meaning, please refer to Table 2.

Table 4*: Competitors' benchmarking results*

Criteria	Notion AI	Fireflies.ai	Coda	
Productivity Gains	5	4	4	**13**
Workflow integration	5	4	5	**14**
Domain template	4	1	3	**8**
Transparency & Safety	4	3	3	**10**
Value for money	4	3	4	**11**
Total	**22**	**15**	**19**	

CPM scores come from vendor documentation, Notion's integrations, templates, pricing, and AI trust/privacy pages; Fireflies' integrations, pricing, security, and help centre; and Coda's integrations, templates, pricing, and security,(Notion, n.d.-a, n.d.-b, n.d.-c, n.d.-d; Fireflies.ai, n.d.-a, n.d.-b, n.d.-c, n.d.-d; Coda, n.d.-a, n.d.-b, n.d.-c, n.d.-d *).*

The result concludes that Notion AI win in terms of score; however, it implies that Notion AI provide a well-rounded experience, but it still lacks structured data automation when compared to Coda. Fireflies.ai can do a real-time transcript and directly integrate with Zoom, Teams and Google Meet.

The objective of the competitor analysis is to identify opportunities; therefore, I will focus on the total score of each criterion. The lowest total criteria score is the Domain template and Transparency safety. The white space lies in domains that are not only a blank template, but an AI built to specialise in industries such as legal contracting drafts for lawyers or a quarterly financial report for accountants.

The transparency and safety gap is equally critical. None of the analysed competitors achieved the highest score of 5. According to the conceptual framework by Zlateva (2024), transparency, including how outputs are generated and the data used for training, must be explicitly stated, while bias must also be disclosed. Notion AI cannot provide this level of transparency because it uses a closed-source API from OpenAI. In addition, the AI surely enables users to control AI behaviour, such as the style (bullet or table), or toggle between precise and perspective-rich answer styles.

4.10 Go-to-market strategy

I applied the 4Ps marketing mix (product, price, place, and promotion) to develop a go-to-market strategy. This will translate segment characteristics and positioning into an actionable plan. The summary of 4Ps is shown in Table 5.

Table 5: 4Ps marketing mixes

4Ps	Strategy
Product	• A self-service GenAI productivity platform with a core feature for all users, such as summarisation of meeting notes and document drafting. • Optional feature for premium tier offers a specialised industry template, for example, a legal drafting assistant, a financial reporting tool with a connection and API to Microsoft 365, Google Workspace • The foundation is built on an open-source model like Llama 3 to support transparency.
Price	• Free plan – for productivity and general template • Specialised plan - $8-$10 per month, competitive with Notion AI and Fireflies.ai
Place	• Direct SaaS distribution via company website with self-serve onboarding. • Integration into professional software ecosystems (e.g., Microsoft 365, Google Workspace • Partnerships with legal and financial institutions (B2B) to validate compliance workflows and gain trust endorsements. Targeted channel sales to professional associations (law, accounting, consulting) for enterprise adoption.
Promotion	• Communicate efficiency and domain-specific knowledge, for example, a short case study before and after time save. • Highlight the importance of an open-source model that is transparent and how the output is being generated (reasoning step), and state what data is being trained on.

4.10 Key Takeaway: Results

Four segments emerge with distinct attitudinal profiles and statistically significant patterns in benefits/concerns. Pragmatic Enthusiasts are the primary target, followed by Emerging Cautious Optimists, based on market attractiveness and adoption readiness. The final product to attract these segments is a self-serve productivity app in freemium plus optional premium industry templates, with 365/Workspace integrations.

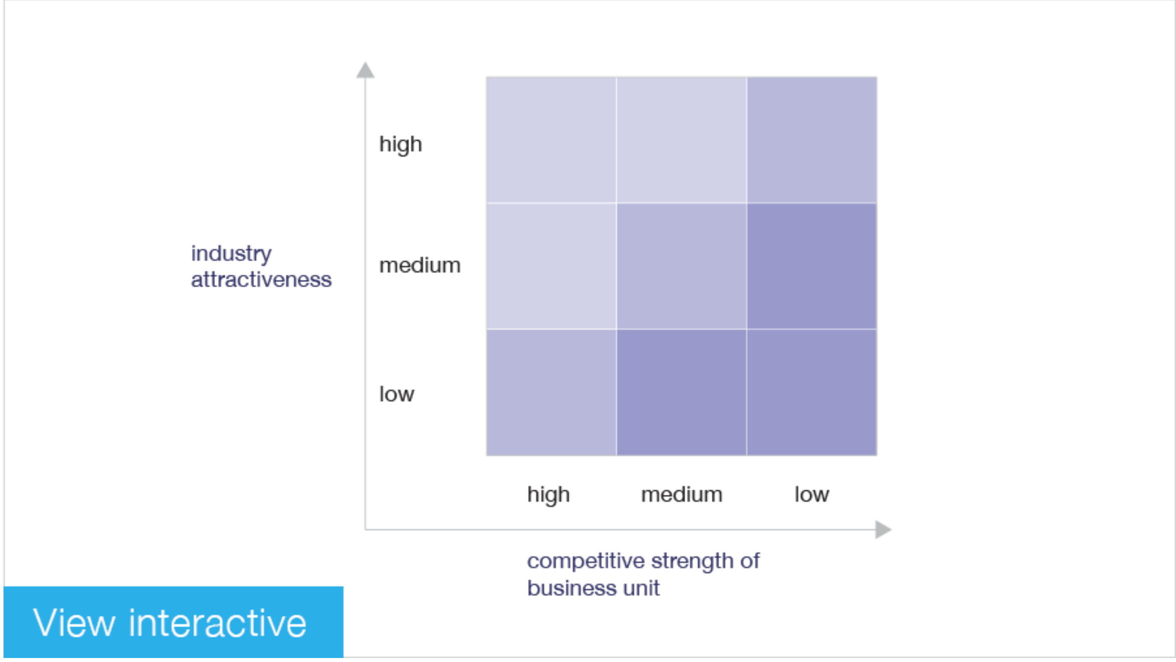
5. DISCUSSION: RESULTS VS. LITERATURE

This study's segmentation results ranges from those who remain sceptical (“Risk-averse Sceptics”) in GenAI to those who are open to using it (“Proficient Pragmatic Enthusiasts”). This result aligns with several studies on GenAI segmentation in higher education. Beckman et al. (2025) identified novice, cautious, and enthusiastic users, while Koteczki & Balassa (2025) found AI sceptics, moderately open users, positive acceptors, and AI innovators. Although this study aligns with my segment results, the study's aim differs. Therefore, I have added experience, trust in AI, and demographics to create nuance in each segment.

Referring to Figure 8, I have modified the GE matrix from Palmatier & Sridhar (2021, p. 56), which extends beyond the original McKinsey GE matrix in Figure 10. McKinsey intends that the matrix is used to manage business units by scoring industry attractiveness against firm competitive strengths (McKinsey & Company, 2008). A later marketing strategy book (Palmatier & Sridhar, 2021, p. 56) applied the matrix to the customer level, retaining the axes of attractiveness and competitiveness (Figure 1). For my studies, I customised the competitive strength of the business unit into adoption readiness. This is because startups are small-sized firms that have limited resources (Adekunle et al., 2024) and rarely operate in business units. Then, I calculated an unweighted Z-score to measure the difference between the scales of variables and placed the segment into the matrix.

For perceptual mapping in Figure 9, I have placed segments alongside GenAI tools in the markets, based on the interpretation of tool capabilities, benefits, and concerns, rather than statistical factors. This is because the survey does not provide brand rating scores that could be used for factor analysis. Common Perceptual mapping is constructed through factor analysis and then positioned using factor scores (Gigauri, 2019). Therefore, my approach.

Figure 10: McKinsey's GE Matrix (McKinsey & Company, 2008)



The product results from a 4Ps model, which concludes a self-service approach that balances productivity features with domain-specific solutions and trust-building mechanisms, such as open-source transparency. The product features are tailored to meet the needs of each customer segment. This aligns with Tyrväinen and Selin's (2011) finding that small Software as a Service (SaaS) firms are typically self-service and must adapt to different customer segments and sizes. The pricing structure employs a freemium approach with a premium tier and a transparent subscription, which is typical in SaaS firms among the internet generation. However, this approach may lead to a heavy reliance on the marketing budget to succeed. The sales process (place) should begin with online marketing, but typically closes deals through personal sales. This means that closing deals in specialised industries such as legal and finance requires personal sales.

6. CONCLUSION

The conclusion comprises a summary of the findings and managerial implications, followed by a discussion of the limitations of the results and suggestions for future research.

6.1 Summary of Findings and Managerial Implications

This study aims to reduce the failure rate of GenAI startups by conducting a cluster analysis to segment the broad market into actionable segments, utilising secondary data, “How do people feel about AI?”, and addressing three research questions.

First, what distinct and actionable consumer segments exist among the UK's GenAI end-users based on their attitudes, behaviours, and concerns about GenAI? The detailed answer can be found in section 4.1 (Segment results). The data reveal four distinct segments: Risk-averse Sceptics, those who are in doubt and view GenAI as a risk, and are not open to using it. Emerging Cautious Optimists are those who recognise efficiency in GenAI but stay alert to bias and data privacy. Passive, Unconcerned Observers are those who feel distant from GenAI, as they have no concern, but are still not open to using it, because GenAI does not play a role in their lives. Proficient Pragmatic Enthusiasts are those who recognise the high potential of GenAI and utilise it to generate recommendations and enhance efficiency in their professional work.

Second, which user segment offers the most significant market potential for a generative AI productivity platform, and how should the GenAI platform be positioned to maximise adoption and differentiation? The detailed answer can be found in sections 4.6 – 4.8. The result from the Z-score plotted in the modified GE matrix indicates that Proficient Pragmatic Enthusiasts are the primary target, and Emerging Cautious Optimists are the secondary target. Positioning for Proficient Pragmatic Enthusiasts is a domain-specific GenAI platform that prioritises efficiency. For Emerging Cautious Optimists, the focus shifts to transparency, data privacy, and unbiased response.

Third, how can these segmentation insights be translated into a targeted marketing strategy (4Ps marketing mix) for a new GenAI startup? The detailed answer can be found in sections 4.9-4.10. The outcomes of competitor analysis (CPM) suggest that domain-specific templates and transparency are opportunities in the GenAI productivity area. The recommendation of 4Ps suggests a GenAI that integrates with industry-specific workflows, such as finance and legal, built on a transparent, open-source model. Offer both freemium and professional tiers at a competitive price, with a SaaS service that integrates with Microsoft 365/Google Workspace and has partnerships in legal/finance. For promotion, communicate efficiently and streamline workflow with before/after productivity shift for

Proficient Pragmatic Enthusiasts, and provide transparent and responsible AI messaging for Emerging Cautious Optimists.

6.2 Results limitation

First, as mentioned in Section 3.11 of the Risk and Limitation section, the sample from the Ada Lovelace Institute survey is biased toward the elderly and higher-income individuals when compared to the UK population. This may result in a lower user experience, as those who intensively use GenAI are predominantly young adults (Figure 3). Second, the perceptual mapping uses conceptually defined rather than factor scores. So the axes and distances are illustrative, not statistical proof, and they can change depending on how I scale them. This risk is foreseen in section 3.11, as the limitation of using the secondary survey. Third, Cluster validation in Section 3.5 yields a silhouette score of 0.153, indicating that poor clusters may arise from mixed datasets with nominal/ordinal variables (Coombes et al., 2021). However, the segments reveal statistical differences in the core attitude segment, and the characteristics align with the empirical study mentioned in Section 2.5.1 of the literature review, which I consider a meaningful and actionable form of marketing strategy.

6.3 Future research

The outcome of the 4Ps analysis indicates that product design and communication should be tailored to domain-specific needs, such as providing financial and legal templates, workflow, and tool integration with existing tools. However, this dissertation does not provide industry-level insight. To understand the actual workflow and tools usage, future research should conduct deep market research. A qualitative approach, such as a focus group or an in-depth interview with professionals in the industry, would provide insight into users' journey, needs, pain points, and adoption barriers. Startups value these insights to train GenAI and design communication tailored to the industry.

To further strengthen the competitor profile matrix (CPM), quantitative research could be conducted to validate the brand score using consumer insight. This involves designing a structured questionnaire, where respondents rate brand performance according to the same CPM factors (e.g., productivity, integration, templates, transparency, value). The result could be used to verify consumer perception and derived weight.

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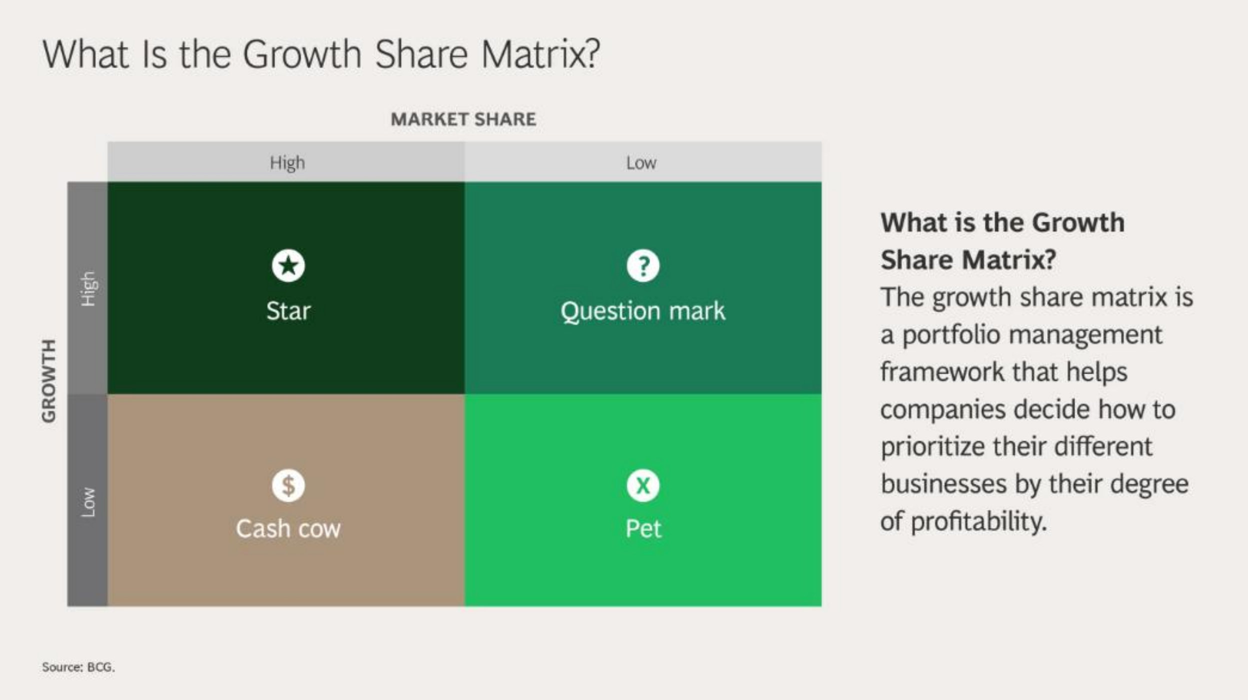
ii. APPENDIX A (Figure and table)

Figure A1 : BCG's matrix



What Is the Growth Share Matrix?

What is the Growth Share Matrix?

The growth share matrix is a portfolio management framework that helps companies decide how to prioritize their different businesses by their degree of profitability.

Source: BCG.

Figure A2 : Hierarchical cluster result

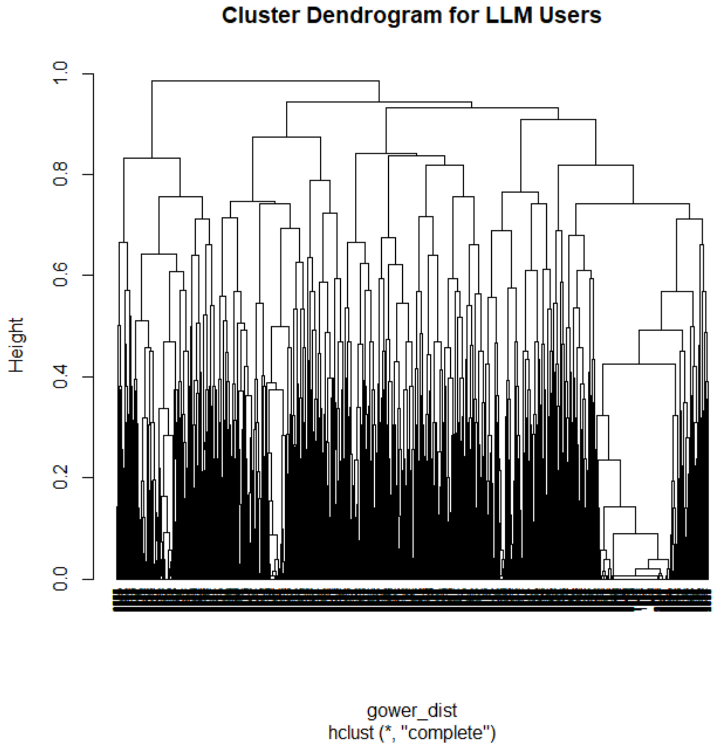


Table A1: Silhouette score by cluster

Number of clusters	*Average Silhouette score*
2	*0.152*
3	*0.136*
4	*0.153*
5	*0.123*
6	*0.126*
7	*0.120*
8	*0.116*

Table A2: Demographic by segments

	cluster	1	2	3	4
	size_percent	21.58	16.82	37.86	23.74
Gender	Female	53.8	50.6	57.2	49.3
	Male	46.2	49.4	42.8	50.7
Age	18-29	7.9	8.2	5.7	9
	30-39	11.9	19.1	12.6	18.9
	40-49	15.6	17.4	17.5	18.6
	50-59	17.2	17.7	18.8	19.7
	60-69	20.3	15.6	19.1	15.3
	70+	27	22	26.4	18.5
Household Income	£1,410 or less pm	19	17.9	22.6	12.8
	£1,411 - £2,560 pm	25.2	21.9	25.4	21.1
	£2,561 - £4,350 pm	25.2	27.7	27.5	29.9
	£4,351 or more pm	30.6	32.4	24.5	36.2
Education	Degree or equivalent, and above	50.7	55	33.6	58.1
	A levels or vocational level 3 or equivalent and above, but below degree	20.5	17.3	19.6	18.4
	Other qualifications below A levels or vocational level 3 or equivalent	20.1	17	29.2	17.1
	Other qualification	0.1	0.7	0.5	0.4
	No qualifications	8.6	10	17.1	6
Region	North East	4	3.4	5.2	3.6

	North West	10.3	9.6	11.4	11.2
	Yorkshire and The Humber	6.3	7.8	10.3	8.8
	East Midlands	8	7.4	7.4	6.7
	West Midlands	9.5	9.3	10.2	8.8
	East of England	6.5	9.8	7.4	7.9
	London	13.6	16.9	10.8	15.8
	South East	16.4	14.2	12.9	13.5
	South West	7.9	8.3	7.4	7
	Wales	5.3	3.9	4.9	4.4
	Scotland	7.8	6.1	6.9	8.2
	Northern Ireland	4.5	3.2	5.1	4.2
Race	White British	75.7	68.6	77	66.3
	Any other White background	7.7	7	5.5	6.2
	Mixed or multiple ethnic groups	2	0.7	1.4	1.3
	Asian or Asian British	9.6	15.9	9.8	17.3
	Black or Black British	4	6.3	5.2	7.8
	Other	0.9	1.6	1.1	1.1
Political party	Conservative	16.4	14.1	18.6	19.1
	Labour	22.2	23.7	18.2	23.5
	Liberal Democrat	5.6	5.2	3.1	5.9
	Other	17.6	13.2	12.1	13.3
	None	38.1	43.8	48.1	38.2
Working class	Middle class	43.2	45.1	32.4	42.6
	Working class	50.7	49.6	62.7	53.9
	Other	6.1	5.3	5	3.5
Status	Married/civil partnership/living with partner	64.8	64.8	67.7	73
	With a partner you do not live with	2.3	3.7	2.5	2.8
	Separated/divorced	8.8	9.2	9.8	6.5
	Widowed/surviving partner from a civil partnership	7.6	6.8	6.6	4
	Single (never married/never in a civil partnership)	16.6	15.5	13.4	13.8
Property right	Owns: outright, buying, shared ownership	78.5	72.4	71	75.5

	Rents from local authority	7	7.2	9.9	5.5
	Rents from housing association/charitable trust	4.1	4.1	7.3	4.3
	Rents privately	10	15.9	11.2	14.3
	Other	0.4	0.5	0.7	0.4
labour-market status	Full time education	2.8	2.2	1.2	2.3
	Paid work	48	53.7	46.2	58
	Unemployed	2.3	2.7	3.2	2.4
	Retired	30.2	24.8	29.5	22.7
	Other	16.8	16.5	19.8	14.6
Job class	Managerial & professional occupations	58.4	58	50.2	63.1
	Intermediate occupations	9.8	10.2	11.9	9.1
	Small employers & own account workers	6.7	6.8	6.8	6.6
	Lower supervisory & technical occupations	8.6	9.1	8.7	9
	Semi-routine & routine occupations	12.9	12.2	14.9	8.5
	Not classifiable	3.6	3.7	7.4	3.6
Subjective financial wellbeing	Living comfortably	17.8	15.3	15.1	16.1
	Doing alright	40.1	41.9	36.3	43.9
	Just about getting by	26.7	29.2	33.2	25.7
	Finding it quite difficult	10.8	8.6	10.3	9.5
	Finding it very difficult	4.5	5.1	5.1	4.8
Household composition	Single person household	21.5	20.5	20.5	15
	One adult (with children)	1.9	1.9	3.9	2.4
	2 adults (no children)	38.6	38.9	39.5	37.8
	2 adults (with children)	15.9	20	17.5	22.3
	3+ adults (no children)	15.2	13.4	12.3	14.9
	3+ adults (with children)	6.9	5.4	6.3	7.6

Table A3: AI readiness and trust by segments

	cluster	1	2	3	4
	size_percent	21.58	16.82	37.86	23.74
Experience using LLMs	To search for answers to questions or for recommendations	2.24	2.97	2.28	3.08
	For entertainment purposes such as creating images/videos or audio clips	1.70	2.22	1.91	2.27
	For educational purposes	1.82	2.55	2.02	2.65
	To support job applications	1.52	2.06	1.79	2.16
	For assisting with everyday work tasks such as writing emails	1.74	2.44	1.98	2.64
	For guidance on issues such as legal disputes, benefits claims, or taxation	1.64	2.05	1.86	2.16
Other benefit	AI Benefit: Face Detection	3.22	3.44	3.47	3.57
	AI Benefit: Cancer Diagnosis	3.38	3.58	3.40	3.56
	AI Benefit: Loan Approval	2.56	2.74	2.68	2.91
	AI Benefit: Wellbeing Monitoring	2.27	2.59	2.58	2.74
	AI Benefit: Smart Chatbots	2.06	2.41	2.29	2.55
	AI Benefit: Robotic Caregiving	2.48	2.81	2.53	2.92
	AI Benefit: Autonomous Cars	2.21	2.60	2.24	2.68
Public share data concern	Concern About Data Sharing with AI	3.51	3.38	3.25	3.18
Comfort to use AI to make decision	Comfort with AI Making Decisions	1.87	2.14	2.13	2.35
AI harmful frequency	AI Harm: Promoting Harmful Content	1.63	1.72	1.57	1.67
	AI Harm: Spreading False Info	2.10	2.17	1.95	2.14
	AI Harm: Financial Fraud	2.06	2.09	1.98	2.13
	AI Harm: Deepfake Images	1.90	1.96	1.75	1.95
	Overall Concern About AI Harm	3.66	3.64	3.39	3.51
Importance of government	Want Monitoring of AI Risks	1.14	1.12	1.21	1.19
	Want Safe AI Development	1.12	1.11	1.19	1.16
	Want Public Access to AI Info	1.18	1.17	1.26	1.23
	Want Unsafe AI Products Stopped	1.07	1.07	1.14	1.10
Digital skills	Search engine	94%	93%	90%	96%
	Revisit website	91%	90%	85%	94%
	Download/save photo	77%	81%	71%	85%

	Send message online	93%	92%	88%	96%
	Share/comment online	73%	79%	65%	83%
	Buy online	89%	89%	85%	93%
	Install apps	79%	82%	72%	87%
	Verify online info	63%	70%	53%	72%
	Solve digital problem	69%	77%	59%	81%
	Fill forms with personal details	87%	86%	81%	92%
	Edit media (image, video)	39%	47%	35%	52%
	None of the above	3%	5%	3%	1%
	Don’t know	0%	0%	0%	0%
	Prefer not to answer	0%	0%	0%	0%

Table A4: Z-score calculation

	cluster	1	2	3	4
Adoption readiness	Positive	-0.19245	0.039405	-0.21011	0.140358
	Negative	0.236932	0.133943	-0.13679	-0.0962
		-0.42938	-0.09454	-0.3469	0.044153
Market attractiveness	Positive	-0.28743	0.272946	-0.17778	0.334017
	Negative	0.346545	0.437328	-0.40503	0.003664
		-0.63398	-0.16438	-0.58281	0.330353

Table A5: GenAI platform classification using the qualitative rubric

Brand	Primary use-case category	X-axis rating	Y-axis rating	Quadrant	Note
Perplexity	Research/Q&A	General	Specialised	**Upper left**	Research-centric assistant; retrieval/citations vs coding.
You.com	Research/Q&A	General	Specialised	**Upper left**	Aggregated search + apps; user-facing, research-oriented.
NotebookLM	Research/Study	General	Specialised	**Upper left**	Study/workspace tied to sources; non-technical users.
Google Veo	Media generator (video)	General	Specialised	**Upper left**	Creative media creation; no coding.
Midjourney	Media generator (image)	General	Specialised	**Upper left**	Creative image generation for designers/creators.
Suno	Media generator (audio)	General	Specialised	**Upper left**	Music/audio generation; creative vertical.
ElevenLabs	Media generator (voice)	General	Specialised	**Upper left**	Speech/voice synthesis; creator/pro vertical.
Notion	Productivity/workspace	General	Mixed → Specialised	**Upper left**	Team knowledge/workflows; non-technical but work-specific.
Fireflies.ai	Productivity (meetings)	General	Specialised	**Upper left**	Meeting capture/notes for teams; domain-like workflow.
Otter.ai	Productivity (meetings)	General	Specialised	**Upper left**	Transcription/notes; work meeting focus.
Coda	Productivity (docs/apps)	General	Mixed → Specialised	**Upper left**	Work OS/docs with automations; non-dev users.
Motion	Productivity (scheduling/PM)	General	Specialised	**Upper left**	Scheduling/PM assistant; work vertical.
GitHub Copilot	Coding assistant	Technical	Specialised	**Upper right**	Developer IDE/code completion; programming domain.

AlphaCode	Coding/competitive programming	Technical	Specialised	**Upper right**	Developer/model focus; code problem-solving.
Amazon CodeWhisperer	Coding assistant	Technical	Specialised	**Upper right**	Developer tool, AWS ecosystem; programming domain.
Harvey	Domain-specific (legal)	Technical (light)	Specialised	**Upper right**	Legal workflows; profession-specific with tools.
Elicit	Domain-specific (research)	Mixed	Specialised	**Upper right**	Research workflows (papers, evidence); pro focus.
Kensho	Domain-specific (finance)	Technical (light)	Specialised	**Upper right**	Financial analytics/tools; pro domain.
PubMed GPT	Domain-specific (biomed)	Mixed	Specialised	**Upper right**	Biomedical literature workflows; pro domain.
OpenAI (ChatGPT/API)	General LLM APIs	General	Broad	**Lower left**	Broad audience/chat; also API but mass-market UI.
Gemini	General LLM APIs	General	Broad	**Lower left**	Broad chat/productivity surface across Google.
DeepSeek	General LLM APIs	General	Broad	**Lower left**	General-purpose model/chat positioning.
Claude	General LLM APIs	General	Broad	**Lower left**	General assistant/writing; broad adoption.
Llama (Meta)	Open-source general writing	Technical	Broad	**Lower right**	Model family for builders; broad use but dev-centric.
BLOOM	Open-source general writing	Technical	Broad	**Lower right**	Open model stack; for builders/researchers.
Anthropic (models)	“Open source general writing” (as mapped)	Technical	Broad	**Lower right**	Used by builders via APIs; your map places here.

iii. APPENDIX B (GenAI prompt)

Description	Model	Prompt
Significant testing table result	ChatGPT-5	[insert all R code of cluster analysis before this prompt] “Return one fenced R code block, no prose. Data = df_final; factor Segment with 4 levels exactly: ‘Risk-averse Sceptics’, ‘Passive Unconcerned Observers’, ‘The Emerging Cautious Optimists’, ‘Proficient Pragmatic Enthusiasts’. Continuous: BenLLM_Score, ConLLM_Score, EXP_LLM. Categoricals = columns matching ^(ben_|con_|dem_). Use only tidyverse, car, rstatix, writexl. 1. One-way ANOVA per score + checks (QQ/Shapiro residuals, Levene); report means/SD, F/df/p, partial eta²; Tukey HSD. 2. χ² for each categorical vs Segment (simulate.p.value if any expected<5), Cramer’s V; if p<.05, pairwise prop tests (BH). 3. One-sample t-tests: each segment mean vs overall mean for the three scores; report t/df/p, Cohen’s d; BH. Export to Significant test result.xlsx with sheets: ANOVA, Tukey, ChiSquare, Pairwise, OneSampleT, SessionInfo. Print file.exists("Significant test result.xlsx") and names(openxlsx::getSheetNames("Significant test result.xlsx")) at the end.”
		generate me hyper realistic of this a person working on GenAI
		[copy and paste cluster persona] can you generate me hyper realistic of this persona.

		[copy and paste cluster persona] can you generate me hyper realistic of this persona.
		[copy and paste cluster persona] can you generate me hyper realistic of this persona.
		[copy and paste cluster persona] can you generate me hyper realistic of this persona.
		Generate me a hyper realistic image of focus group
		Generate me an image that represent productivity genAI product

		Generate me of the pilot launch image

iv. APPENDIX C (Proposal)

Large language model end-user segmentation to define opportunities and Go-to-market strategies for startups and AI innovators

Cover Sheet	
Module Code	BEMM466
Module Name	Business project

Within the Business School we support the responsible and ethical use of GenAI tools, and we seek to develop your ability to use these tools to help you study and learn. An important part of this process is being transparent about how you have used GenAI tools during the preparation of your assignments.

The below declaration is intended to guide transparency in the use of GenAI tools, and to assist you in ensuring appropriate referencing of those tools within your work.

The following GenAI tools will use in the production of this work:

[please specify] GPT-4o, Gemini pro 2.5

☒ *I will use GenAI tools for brainstorming ideas.*

☐ *I will use GenAI tools to assist with research or gathering information.*

☒ *I will use GenAI tools to help me understand key theories and concepts.*

☒ *I will use GenAI tools to identify trends and themes as part of my data analysis.*

☒ *I will use GenAI tools to suggest a plan or structure of my assessment.*

☒ *I will use AI tools to give me feedback on a draft.*

☐ *I will use GenAI tool to generate images, figures or diagrams.*

☒ *I will use AI tools to proofread and correct grammar or spelling errors.*

☐ *I will use AI tools to generate citations or references.*

☒ *Other [please specify] Debugging code*

☒ *I declare that I have referenced use of GenAI tools and outputs within my assessment in line with the University referencing guidelines.*

Synopsis

This project consultancy style report is designed to address a challenge in doing targeted marketing in the fast-moving pace, large language models market. The project has three primary objectives: to identify and quantify distinct user segments based on their attitudes and behaviors; to understand the motivations and barriers that define each group; and to develop actionable market entry strategies for startups and AI innovators. To achieve this, this study will use quantitative analysis from secondary data from Ada Lovelace Institute's November 2024 survey on public attitudes to AI, which includes 3,513 UK respondents. The primary methodology will involve cluster analysis to create segmentation, followed by the application of marketing frameworks such as brand positioning mapping and the 4Ps to provide market entry strategies.

Problem statement and objectives:

Large language models (LLMs) such as ChatGPT, Gemini, Copilot, have rapidly integrated into daily life from personal support to technical assistance. Despite the introduction of numerous new models over the past few years, the industry still struggles to define clear and actionable user segments. This knowledge gap presents a significant challenge for product developers to prioritize features and for marketers to craft tailored messages in this dynamic market.

For startups and AI innovators, this challenge is critical. Startups often operate with limited resources (Adekunle et.al, 2024) and the need for rapid adoption makes it even harder to identify the right target. This makes it difficult for them to create the product-market fit solution (Bilow, 2025) and compete with the big tech companies. Therefore, this consultancy project aims to address this critical issue by answering the following research questions:

1. What distinct and actionable consumer segments exist among the UK's large language modes (LLMs) end-user based on their attitudes, behaviors, and concerns?
2. What are the key motivations (perceived benefits) and barriers (perceived risks and concerns) that characterize each of these identified segments?
3. How can these segmentation insights be translated into a targeted market entry strategy (including positioning and a 4Ps marketing mix) for a new AI innovator?

These research questions will provide significant value to startup and AI innovator. First it will give an academic understanding based on theoretical perspective combining with a data-driven segmentation approach. This will help startups identify high-potential users based on their functional and attitudinal motivation, understand competitive landscape, and finally decide the right marketing strategies.

Literature review

This literature review explores three core topics to build a foundation for research. The review will begin with the literature of traditional segmentation using the foundational academic book, Marketing Strategy: Based on First Principles and Data Analytics (Palmatier & Sridhar, 2021). This literature will show the why segmentation is matter and how to perform a correct segmentation. Next, I will examine into a recent tech segmentation paper Consumer Segments in Blockchain Technology Adoption, (Tanković et.al, 2023). This is to show how segmentation has been used to understand adoption behavior for emerging technologies (like blockchain, which is conceptually similar to generative AI in being new technology).

Following this, the review will address the reason why people adopt new technology through Technology Acceptance Model, as detailed in "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology" (Davis, 1989), will be used to understand the functional motivations of users. This will be supplemented by the more comprehensive "Unified Theory of Acceptance and Use of Technology (UTAUT)" (Venkatesh et al., 2003), which incorporates additional factors like social influence. These literature sources provide essential context for understanding why people adopt new technology, thereby making the analysis more robust and credible.

Finally, the report will explore literature of ethical and privacy dimensions of AI adoption from "Artificial Intelligence (AI) Ethics: Ethics of AI and Ethical AI" (Siau & Wang, 2020) to understand the barriers and concerns that shape user behavior. This paper highlight privacy, transparency, bias, and accountability of AI. Understanding these issues will help analytical process to be more nuanced and ensure that segmentation insights align with ethical concerns and user trust.

Data source

The main data for cluster analysis will use secondary data from “How do people feel about AI?” survey project. This research was led by the Ada Lovelace Institute (Ada Lovelace, 2024) a research institute focused on data and AI for society, in partnership with The Alan Turing Institute. The data is from the second wave of the survey which was conducted in November 2024 with 3,513 respondents.

The methodology of survey is conducted through The NatCen Opinion Panel which sources its participants from the highly regarded British Social Attitudes Survey (BSA) and the Life in Northern Ireland survey (LNI). A mixed-method approach was applied for data collection through majority of online surveys and a smaller potion

conducted by phone. The sampling design was constructed to ensure a balanced of respondent's profile. In addition, the sample included a booster of specific demographic such as those who have low digital literacy, low financial literacy, and some ethnicity background. To guarantee the accuracy of the results, statistical weighting was applied at the recruitment, sampling, and survey stages.

Ethical considerations

The secondary data from Ada Lovelace Institute is anonymous as there is no personal information such as name, phone number, address present in the data. This ensures compliance with ethical standards and data protection regulation. Additionally, the NatCen Opinion Panel adheres strictly to ethical and privacy guidelines such as asking permission and skip to personal information, keeping the data safe according to GDPR (NatCen, n.d.). This outlined how participant data is securely managed throughout the research.

Regarding the analysis stage, the focus will shift toward algorithmic bias in the clustering process. This is because segmentation can sometimes cause unintentionally overlooking demographic or attitude. To mitigate this risk, the analysis will be carefully reviewed to ensure no group is unfairly represented. Furthermore, as the final output is a set of actionable marketing recommendations, there is a duty to ensure that these strategies are fair and transparent.

All research activities will be conducted in full compliance with University of Exeter's Research Ethics Framework and the specific guidance for the BEMM466 module. This includes adhering to the data protection and storage protocols, such as using the University of Exeter OneDrive for all data storage and ensuring the complete destruction of the data by the specified deadline.

Proposed methodology

This project will employ quantitative research approach though R, using secondary data from Ada Lovelace Institute's 2024 national survey on attitudes toward AI.

Before the main segmentation analysis, Exploratory data analysis (EDA) will be conducted. This phase is a step to ensure the quality and integrity of the data. The primary objectives of the EDA will be to clean and prepare datasets by handling any missing or duplicate values, and if any encoding is needed. Furthermore, descriptive statistics will be used to understand the basic features of data and to gain initial insight of the demographic and attitude of respondents.

Following the EDA, the core analytics techniques used to create segmentation will be **cluster analysis** (e.g., K-means or hierarchical clustering). The segmentation will be built using behavioral key attitudinal and behavioral variables from the survey that relates to Large Language Models (LLMs). The analysis will be primarily informed by responses to the following key questions:

1. Have you had any personal experience with using **Large Language Models (LLMs** for the following tasks?
2. Which of the following, if any, are ways that you think the use of **Large Language Models (LLMs)** will be beneficial?
3. Which of the following, if any, are concerns that you have about the use of **Large Language Models (LLMs)**?
4. On the whole, how would you rate the **effect** of new technologies on society?

Approaches to analyzing findings

After the EDA process, I will apply the elbow plot method to identify the appropriate number of segments. Each segment will then be named according to its key characteristics, drawing from attitudinal, behavioral, and demographic data. To ensure the final segments are statistically significant difference, I will perform ANOVA test to confirm the distinction. If the identified segments remain not meaningful, human judgement may be used to refine the results, which could involve combining segments that have similar characteristics.

Once the user segments are identified, the finding will be analyzed to create detailed segment profile and to inform actionable business strategies as visualized in Figure1.

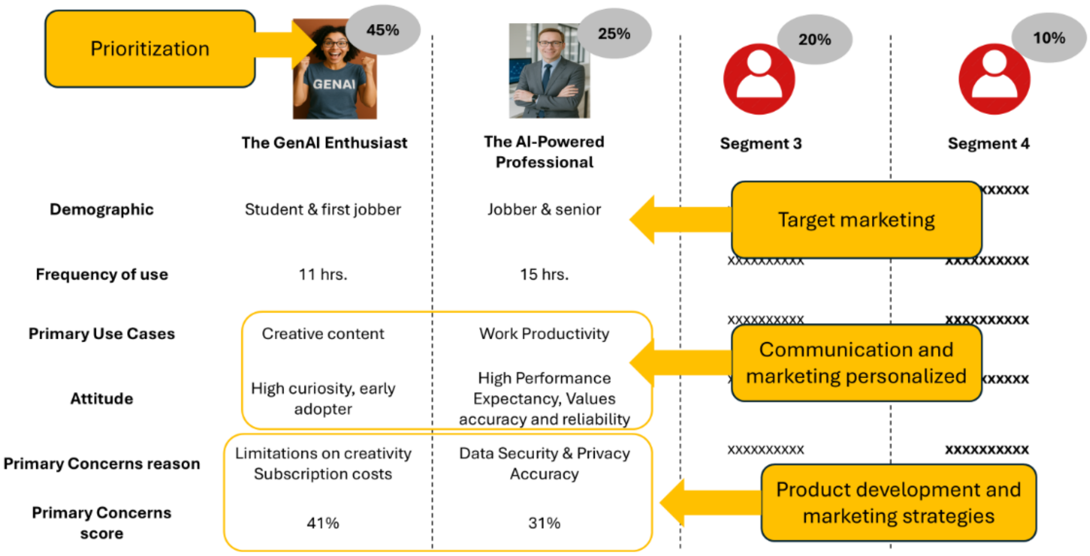


Figure 1: Example output of segmentation

Each identified segment will be built using key variables which I think are core decision making information based on Ada Lovelace Institute's 2024 survey, including demographic such as age group and professional status, behavioral metric including frequency of use and primary use case, additional characteristic mindset towards technology and AI, primary concern and key barriers. Regarding the targeting, I use segment size, accessibility (digital literacy & demographic), and perceived benefits as a key criterion.

As the project is consultancy-style, these insights have to be translated into business actions. The analysis will be designed to directly link the findings to key strategic areas. The size of each segment will help with target prioritization. The demographic data from each profile will inform targeted marketing strategies. Furthermore, understanding the primary use cases and attitudes will allow for the creation of personalized communications. Finally, the barrier to use will guide product features and marketing strategies.

In addition, positioning mapping will be conducted to be recommendation for AI innovator to position itself against competitors. Figure 2 below shows the example output of brand positioning mapping. The figure illustrates the current competitive landscape of LLMs market. The map is structured with two dimensions which X axis represents broad audience versus technical focus, while Y axis represents specialised and general purpose. The map show high opportunity in the Specialised & Broad Audience" quadrant as this space is less dominant player.

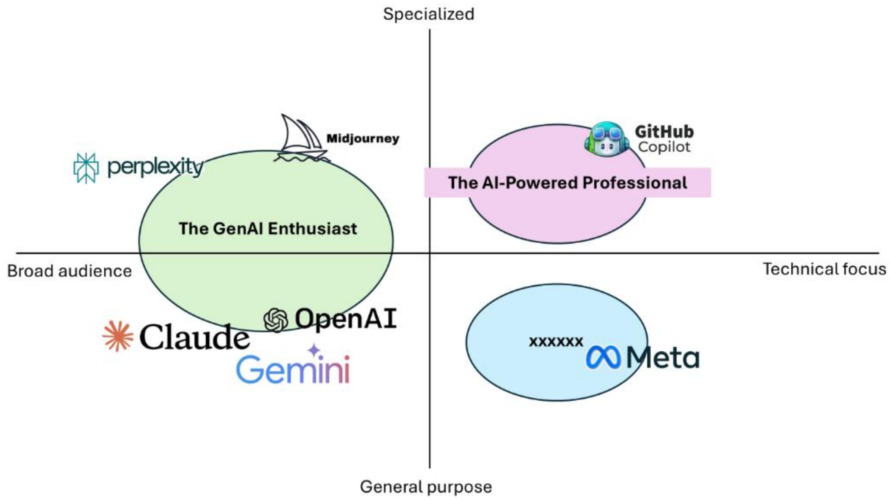


Figure 2: Example output of brand positioning mapping

Finally, the 4Ps marketing framework will be used to combine the analysis into a conclusive market entry strategy. The section will outline the information used for each of the 4Ps, with the corresponding question numbers indicated in brackets. **The Product** section will be defined by analyzing the primary use case (ExpLLM) and current barriers (ConLLMWhich) combining this insight with the strategic positioning mapping to inform the feature and value proposition. **Price** will be determined by a combination of competitors' product analysis and the income of target group. **Place** will be measured through digital access (DigAccess) and digital skills (DigSkills). Lastly, the **Promotion** will be present in twofold: the communication message will be crafted by highlighting the specific benefits valued by the target segment (BenLLMWhich), while the selection of promotional channels will be tailored to the segment's demographic profile, particularly their age and profession.

Limitations

One of the study key limitations is the fast-moving pace of LLMs development. Consequently, the survey was conducted in November 2024, which may risk becoming outdated in the near future. However, this limitation is partially mitigated by the attitudinal segmentation. These attitudes such as perception of risk and benefits tend to shift more slowly than application usage, providing more durable results.

Another foreseeable limitation is that the research is based on a national survey of the UK. As a result, the recommendation entry strategies will be tailored to the UK market. If the user wants to apply the strategies in other countries, further research would be essential to validate user segments and adapt strategies to account for the region’s culture, economics and regulation.

Associated risks

There is an analytical risk related to the interpretation of segmentation. As the data is not designed for marketing segmentation, the resulting segments may not be clearly defined and may not turn into actionable marketing insights (Dibb & Simkin, 2001). To mitigate these risks, I could apply the authors' checklist to ensure that: 1) segments are clearly defined, 2) the startup’s resources can support segmentation, and 3) the segmentation insights inform the product and marketing plan.

Timeline

	June				July				Aug					Sept
	W1 1-7	W2 8-14	W3 15-21	W4 22-28	W1 29-5	W2 6-12	W3 13-19	W4 20-26	W1 27-2	W2 3-9	W3 10-16	W4 17-23	W5 24-30	W1 31-5
Proposal development	■	■												
Proposal and Ethic form submission			17											
Proposal and Ethic form feedback & approval				■										
Literature review					■									
Data preparation & cleaning						■								
Data analysis (segmentation & validation)							■							
Strategic Analysis (Positioning, Targeting, 4Ps)								■						
Draft report writing									■	■	■			
Supervisor's Feedback on Draft											■			
Final report development											■	■	■	
Final report submission														2-3

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