Management Letters / Cuadernos de Gestión (2023) 1-19

FESIDE
Fundación Emilio Soldevilla para la Investigación y Desarrollo de la Economía de la Empresa

enpresa institutua
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Management Letters / Cuadernos de Gestión

journal homepage: https://ojs.ehu.eus/index.php/CG

ISSN: 1131-6837 / e-ISSN: 1988-2157

The role of Passion and Self-Efficacy in entrepreneurial activities in the gig economy: An Unsupervised Machine Learning Analysis with Topic Modeling

El papel de laPasión y la Autoeficacia en las actividades emprendedoras en la Economía gig: Un análisis de aprendizaje automático no supervisado con modelación temática

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ARTICLE INFO

Received 28 February 2023,
Accepted 11 December 2023

Available online 8 February 2024

DOI: 10.5295/cdg.231955ac

JEL: L26; M13; M15

ABSTRACT

This research examines passion and self-efficacy through experience and knowledge, as motivational factors that support entrepreneurs within the gig economy (GE). It sheds light on entrepreneurs' sources of passion in the GE literature. The sample is composed of all the 1164 entrepreneurship activities offered worldwide through Airbnb, Tour by Locals, and Withlocals on 5 May 2022. The study is supported by unsupervised machine learning models and seeks to find latent topics emerging from the analysis of the entrepreneurs' descriptions and exposes the main correlated clustered dimensions. There are six main motivators behind GE platforms as a first step toward entrepreneurship: Experience, Passion for share, Knowledge, Classic traditions, Empowered community and local activities, and Well-being. It also confirms the correlation between passion and self-efficacy through experience, pointing them as main factors behind entrepreneurship in the GE. Five of the six sources of passion previously pointed by theory were found: Passion for growth, for people, for product/service, for innovation and for social mission. This study discloses self-efficacy and the sources of passion and points directions to practitioners involved in entrepreneurial activities in the GE ecosystem. This work used machine learning models to access quantitatively a paradigm that is inductive by nature. The results point to well-being as a significant factor to be addressed in future research regarding entrepreneurship. This research only studies individuals involved in the GE; as such, further studies should cohort new populations from different fields.

Keywords: Gig economy, Entrepreneurship, Passion, Self-efficacy, Content Analysis, Latent Dirichlet Allocation.

RESUMEN

Esta investigación examina la pasión y la autoeficacia a través de la experiencia y el conocimiento, como factores motivacionales que apoyan a los emprendedores dentro de la economía gig (EG). Crea nuevas sobre las fuentes de pasión de los emprendedores en la literatura de la EG. La muestra se compone de todas las 1.164 actividades de emprendimiento ofrecidas en Airbnb, Tour by Locals y Withlocals el cinco de Mayo de 2022. El estudio se apoya en modelos de aprendizaje automático no supervisado trata de encontrar temas latentes que emergen del análisis de las descripciones de esos emprendedores y expone las principales dimensiones agrupadas correlacionadas. Hay seis motivadores principales detrás de las plataformas de EG como primer paso hacia el emprendimiento: Experiencia, Pasión por compartir, Conocimiento, Tradiciones clásicas, Empoderamiento de la comunidad y actividades locales, y Bienestar. También se confirma la correlación entre la pasión y la autoeficacia a través de la experiencia, señalándolas como factores principales detrás del espíritu empresarial en la EG. Se encontraron cinco de las seis fuentes de pasión señaladas anteriormente por la teoría: Pasión por el crecimiento, por las personas, por el producto/servicio, por la innovación y por la misión social. Este trabajo revela la autoeficacia y las fuentes de pasión y señala direcciones a los profesionales implicados en actividades emprendedoras en el ecosistema de la EG. Este trabajo utilizó modelos de aprendizaje automático para acceder cuantitativamente a un paradigma que es inductivo por naturaleza. Los resultados apuntan al bienestar como un factor significativo que debe abordarse en futuras investigaciones sobre el espíritu empresarial. Esta investigación sólo estudia individuos involucrados en la EG; como tal, estudios posteriores deberían cohortar nuevas poblaciones de diferentes ámbitos.

Palabras clave: Economía Gig, Emprendimiento, Pasión, Autoeficacia, Análisis de Contenido, Asignación Latente de Dirichlet.

1. Introduction

Gig economy (GE) platforms act as intermediaries in facilitating peer-to-peer short-term contracts and are widely used by various digital platforms in the sharing and collaborative economy (Broda, 2021; Cho & Cho, 2020). Their impact on entrepreneurial activity is substantial, as they offer valuable solutions for individuals to participate in entrepreneurial landscapes (Anwar, 2018; Scheepers & Bogie, 2020). These platforms operate through transient contractual arrangements, as extensively utilized by diverse digital platforms, and play a crucial role in enabling the exchange of services and products within the economic landscape (Pankov *et al.*, 2021; Schmidt, 2017). The integration of GE platforms is consistently associated with sharing, collaboration, and platform economies (Chalmers & Matthews, 2019; Klarin & Suseno, 2021).

It is imperative to investigate the multifaceted implications of GE on the macroeconomic ecosystem within the business sphere because GE's influence extends beyond the individual level (Allon *et al.*, 2023; Burke & Cowling, 2019). Entrepreneurs participating in the GE are categorized as "independent workers", "gig workers" (GWs), or "freelancers" (Katz & Krueger, 2019; Poon, 2019). These GWs exhibit high autonomy and flexibility in their work arrangements (Ray & Pana-Cryan, 2021), which are integral to the GE (Kost *et al.*, 2020; Turner, 2023).

Within this context, GWs emphasize the episodic nature of their work engagements, reflecting the notion of conducting discrete gigs or tasks, often for various clients or platforms (Larsson & Teigland, 2020). Similarly, freelancers underscore their status as independent contractors who offer expertise and services on a project-specific basis. These designations collectively capture the essence of the GWs, where individuals not only embrace but also thrive on the values of independence and flexibility, which are central tenets of their professional pursuits.

Even in low-income countries, mainly due to the Covid-19 crises, GE has experienced growth and is proposed as a solution for macroeconomic growth and sustainable development (UNCTAD, 2018; United Nations, 2020). The diffusion of technological resources associated with GE's business opportunities can stimulate growth-oriented entrepreneurship, because it encourages GWs to exploit new, healthier and sustainable economic activities (Barratt *et al.*, 2020; Burke & Cowling, 2020). Therefore, it is urgent to assess this ecosystem to understand individuals' motivations for adhering to these platforms and to maintain them as a means of entrepreneurship.

There is scarce empirical evidence in the literature on GWs' motivations to adhere to GE. Economic needs, search for autonomy, solutions for resource constraints due to the low risk of breaking the entry barrier, and emotional affections such as passion are the most cited (Burke & Cowling, 2019). Passion, which refers to one's excitement to adopt a determined action, has shown latent significance towards the intent to adhere to GE for entrepreneurial purposes. Moreover, passion increases an individual's positive feelings towards entrepreneurial actions and is considered a motivational factor that positively affects their decision to become an entrepreneur (Li *et al.*, 2020). Conversely, there are hardly any studies that closely address this matter, pointing to the most significant factors impacting entrepreneurial intent through GE platforms or confirming the affective significance of passion (Vasques *et al.*, 2017).

The entrepreneurship literature supports the idea that passion predicts entrepreneurial intention, entrepreneurial orientation, and the formation of some entrepreneurial behaviors, such as self-efficacy (Norena-Chavez & Guevara, 2020). Similarly, in the GE literature, it is consensual that GWs' belief in their capacities is a decisive motivational factor that translates into self-efficacy (Ravenelle, 2019).

Silva and Moreira (2022) have highlighted the significance of GWs' control over the products they offer and the affectivity of activities mediated through platforms as critical determinants of GE Entrepreneurship. Behaviors and engagement with services on these platforms impact the GW's personal and professional experiences and are amplified by their passion for work (Vasques *et al.*, 2017). GWs are highly motivated to pursue entrepreneurial opportunities in activities they are passionate about while also being conscientious of their control (Gandini, 2016). However, there is a gap in the relationship between passion and self-efficacy towards various entrepreneurial factors, such as social support and entrepreneurial intention, which remain to be explored using different populations and methods of analysis (Cardon & Kirk, 2015).

Although passion has been assessed through its impact on entrepreneurial outcomes, performance, and success, there is a latent need to understand the foundations of an individual's passion (Cardon & Kirk, 2015). Moreover, Cardon *et al.* (2009) and Santos *et al.* (2020) note that it is important to further investigate the types of passion to predict entrepreneurial behaviors individuals engage in without being strictly related to entrepreneurship, such as creativity and perseverance, with consequences for different entrepreneurial ecosystems and all stakeholders involved. Therefore, assuming that individuals involved in GE-based entrepreneurial activities are strongly motivated by passion (Codagnone *et al.*, 2016; Huarng, 2018; Scheepers & Bogie, 2020), and consequently, tend to focus more on their endeavors, this investigation also aims to confirm the sources of passion found among GE entrepreneurs under the conceptualized sources of passion by Cardon *et al.* (2017). Therefore, to address these gaps, this study seeks to answer the following research questions:

- RQ1: What are the main motivators influencing entrepreneurial intention on GE platforms?
- RQ2: Are passion and self-efficacy among entrepreneurial intention motivators in GE platforms? If so, how do they relate to self-efficacy experience and knowledge components?
- RQ3: If passion is one of the factors influencing entrepreneurial intention in GE platforms, what are the types of passion found among these GW?

In this study, we aim to uncover the main motivational factors using a phenomenological approach with a dataset comprising 1164 observations. We utilized a mixed method involving machine learning algorithms to identify factors and relevant keywords based on frequency, which were then labeled. We used topic probabilities associated with these factors in a Principal Components Analysis (PCA) to determine their statistical relationships and correlations. Additionally, we employed an algorithm to assess distributions by gender and innovator type, distinguishing between innovators and non-innovators, which played a central role in interpreting the results alongside other variables.

This paper presents theoretical implications confirming passion and self-efficacy, driven by experience or knowledge, as drivers of GE entrepreneurship. It also reinforces the link between passion and the experiential aspect of self-efficacy while highlighting well-being as a significant motivational factor necessitating further exploration. Furthermore, the framework of passion sources is tested and demonstrates its reliability across various types of passion, while emphasizing the pursuit of knowledge as a new foundation of passion. Notably, women exhibited higher levels of passion and were more prominent in innovation-related aspects.

The study has five sessions. Section 2 reviews pertinent literature on the topic and formulates research hypotheses. Section 3 outlines the methodology, divided into two parts: first, it employs machine learning techniques based on latent Dirichlet allocation to identify emerging factors using topic and keyword frequency analysis; subsequently, it employs the findings from the first part to conduct cluster analysis and PCA to infer factor correlations. Section 4 discusses the main findings and their theoretical and practical implications. Finally, Section 5 concludes the study, offering key insights and acknowledging limitations while suggesting future research directions.

2. Literature review

2.1. Passion, entrepreneurship and GE platforms

Passion, a powerful emotion, impacts motivation toward specific concepts, individuals, objects, or activities and is linked to affection, identity, and the willingness to invest time and energy (Santos *et al.*, 2020). Two primary types of passion exist (Murnieks *et al.*, 2020; Vallerand *et al.*, 2003): obsessive passion, characterized by intense action regardless of outcomes, and harmonious passion, rooted in self-control and meaningful motivation from life experiences. Those with high levels of harmonious passion tend to pursue their goals more objectively than those with lower levels.

In entrepreneurship literature, passion is considered a complementary emotional trait that propels entrepreneurial activities through motivation and integration (Cardon *et al.*, 2017). It is fundamental for achieving business success, encouraging entrepreneurial persistence, and is often referred to as the heart of entrepreneurship due to its constant presence in studies on the entrepreneurial process and creative entrepreneurial intentions (Biraglia & Kadile, 2017). Passion also enhances self-efficacy, vision, and strategic behaviors, ultimately improving opportunity perception and innovative thinking (Cardon & Kirk, 2015).

To investigate how passion's antecedents influence entrepreneurial activity, understanding its sources is essential (Cardon *et al.*, 2009; Clarysse *et al.*, 2015). Cardon *et al.* (2017) identify six main sources of passion: Passion for growth (focused on business development); passion for people (emphasizing stakeholder relationships), passion for products/services; passion for competition (desiring superiority); passion for inventing (motivated by innovation); and passion for a social mission (dedicated to solving problems for underprivileged groups).

The experience of doing something with passion is associated with enjoyment, a key determinant in the GE literature that influences adherence to GE platforms (Liang *et al.*, 2018). GWs are driven not only by the financial benefits of their services but also by the sense of meaningful contribution (Cho & Cho, 2020; Choi & Choi, 2019). Autonomy, flexible schedules, and technological resources provided by GE platforms open doors for GWs to develop themselves and serve as resources for self-improvement (Burke *et al.*, 2019; Ravenelle, 2019). Emotions associated with their activities in this ecosystem play a crucial role in motivating their entry and sustaining their performance (Vasques *et al.*, 2017; Zhang *et al.*, 2019). Consequently, building upon the concepts of the sources of passion motivating entrepreneurship, we propose the following hypothesis linking passion to GE platforms:

H1. Passion is a factor that motivates the intention to entrepreneurship through GE platforms.

2.2. Entrepreneurship, knowledge and GE platforms

In behavioral studies, knowledge is based on previous interactions or dedicated study (Roxas, 2014; Memon *et al.*, 2019). It contributes to one's experiences and life journey. It is closely tied to the process of learning and a practical interplay with a certain matter or subject (Liguori *et al.*, 2018; Sobakinova *et al.*, 2020). Observations and actions lead to unique personal experiences and, consequently, knowledge (Lumpkin *et al.*, 2011). Knowledge and experience are intertwined, as in the entrepreneurial intention literature, where they are vital for the development of self-efficacy (SE), perceived controllability and alertness (Vamvaka *et al.*, 2020).

SE is one of the most studied constructs that comprises the intention towards a behavior, followed by controllability (Ajzen, 2002; Bolton & Lane, 2012; Carsrud & Brännback, 2009). Both are components of perceived behavior control and are influenced by knowledge and experience (Dempsey & Jennings, 2014; Zhao *et al.*, 2005). Accumulated experience builds confidence, and this confidence is supported by internal and external factors, shaping behavioral, normative and control beliefs that guide human behaviors (Ajzen, 2002).

In the entrepreneurship literature, knowledge and experience indirectly influence self-efficacy, due to their affective experiential and instrumental cognitive foundations (Liao *et al.*, 2022). These components play a pivotal role in forming constructs like entrepreneurial intention, entrepreneurial orientation, alertness and attitude towards entrepreneurial behavior, all influenced by passion through affective experiential domains (Pfitzner-Eden, 2016; Wang *et al.*, 2021). Entrepreneurial orientation (EO) studies link entrepreneurial knowledge (EK) and entrepreneurial experience (EE) to positively performance (Santos *et al.*, 2020), innovation and alertness to opportunities (Yitshaki & Kropp, 2016). Yet, EK is highly associated with the development of EO, and affects entrepreneurial growth (Hallak *et al.*, 2011; Wach *et al.*, 2018), although research relating the impact of EK on individual EO is in high demand.

Combining EK and EE significantly improves entrepreneurs' likelihood of success (Roxas, 2014; Sobakinova *et al.*, 2020). Moreover, Wach *et al.* (2018) confirm the impact of EK and EE on performance, highlighting their importance in facilitating business and network building. Recent publications on social capital show that entrepreneurs developing EK and EE stablish valuable business networks, reinforcing the importance of subjective norms in entrepreneurial intention (Ali & Yousuf, 2019; Liñán & Santos, 2007; Sulistyani *et al.*, 2022).

EK and EE drive the adoption of GE platforms in entrepreneurship, influenced by self-efficacy. GWs' activities rely on their experience and knowledge, reducing entry barriers related to finances, support, and networks (Belk, 2014; Netto & Tello-Gamarra, 2020; Trabucchi *et al.*, 2019). GE platforms serve as facilitators, enhancing perceived controllability and reducing fear of external factors, increasing knowledge acquisition and benefiting self-efficacy (Burtch *et al.*, 2018). Slack resources contribute to platform-based knowledge/experience (Klarin & Suseno, 2021). More connections lead to increased EK and EE, forming the basis for self-efficacy and perceived controllability (Silva & Moreira, 2022). Furthermore, GWs are involved in entrepreneurial activities on GE platforms not only for economic reasons but also due to emotional factors like passion, which positively influence entrepreneurial intention, self-efficacy and alertness. Based on this, the following hypotheses are proposed and presented in Figure 1:

H2. The relationship between GWs and GE platforms contributes to the development of self-efficacy through experience (SEE).

H3. The relationship between GWs and GE platforms contributes to the development of self-efficacy through knowledge (SEK).

H4. GWs' self-efficacy through experience (SEE) correlates with passion.

H5. The self-efficacy of GWs through knowledge (SEK) correlates with PA.

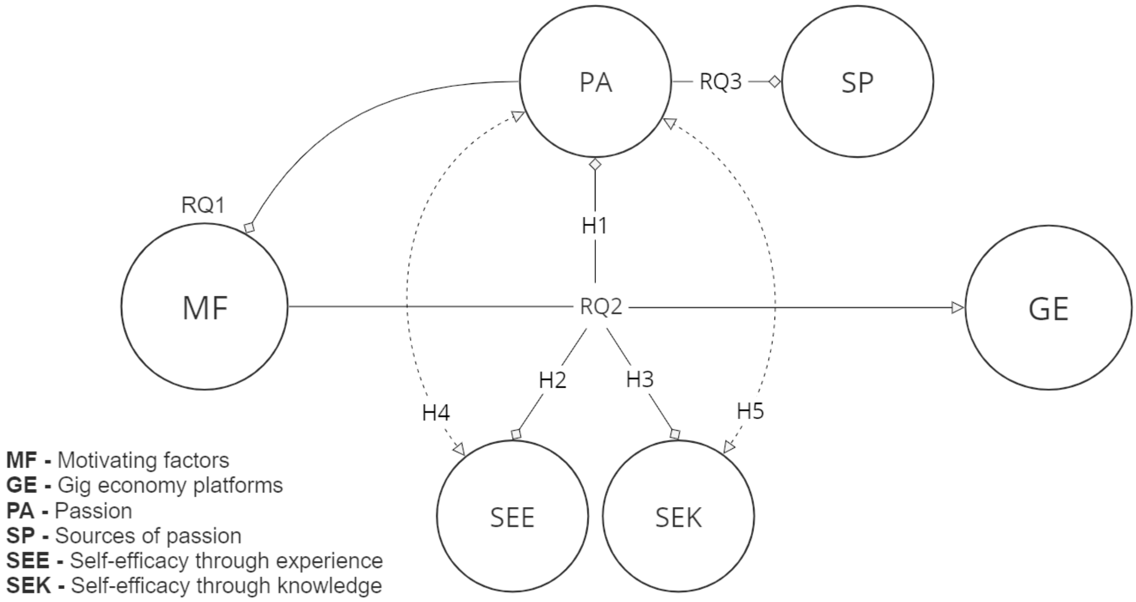

Figure 1
Research model of the investigation
Source: Own elaboration.

3. Methodology

3.1. Main steps

To ensure precision, a two-step phenomenological approach (Cardon *et al.*, 2017) was executed in R for machine learning. This open-source software, utilized for statistical analysis and visualization, enabled the inference of statistically significant factors (R Core Team, 2022). Machine algorithms automatically determine topics and their meanings, enhancing machine learning's robustness in this research. Step one encompassed online data collection, including temporal, gender, product offerings on GE platforms, and "about me" textual profiles, inveigling motivations. The analysis combined deductive unsupervised machine learning and inductive qualitative methods to identify core latent topics.

The second step entailed assessing the relatedness between the identified themes and the theoretical definitions proposed by Cardon and Kirk (2015) and Cardon *et al.* (2017). The topics derived from users' descriptions were contrasted with theoretical frameworks to proxy sources of passion and self-efficacy through experience and knowledge. Additionally, the definition of innovation —based on Yuan *et al.* (2016), to find solutions through technology to solve problems combining new applications with existing resources— was employed to evaluate passion for growth, passion for products, and passion for inventing. GWs have shown availability, transforming their online service delivery through technical solutions and altering elements of the previous model/system (Liang *et al.*, 2018). Therefore, the user's start date and number of offers on the platform were used to proxy innovation using binary codes (innovators or non-innovators). Innovators were those providing diverse experiences and those who registered prior to March 2020, coinciding with the OMS's confirmation of the Covid-19 pandemic and the introduction of online features by GE platforms.

3.2. Data collection and Sample

The data collected in this research closely mirror the approach used by Williamson *et al.* (2022), which employed secondary data for netnographic analysis. Specifically, on May 5, 2022, we accessed the platforms Airbnb, Tour by Locals, and Withlocals to gather user descriptions related to their tourism services. Our data collection was exhaustive, encompassing information from openly accessible profiles worldwide at that time, without any specific language or demographic restrictions. This comprised 40.9% men, 53.8% women, 5.1% couples (2 individuals), and 0.3% groups (more than 3 individuals).

The scraping technique was used to optimize the collection. This method utilizes a pre-defined algorithm to systematically navigate through pages and extract the relevant data (Ferrara *et al.*, 2014), encompassing all online tourism experiences offered on the three websites. The data retrieved from these sources yielded 1173 observations and six variables, including name, activity, host, entry date, location, and page link. Subsequently, this data was organized into a table sheet as the initial step in the pre-processing phase. To further refine the data, a CSV file was imported into the R studio environment for the subsequent cleansing process.

3.3. Methods and techniques

This study utilized a mixed methods approach, exploring topics through Latent Dirichlet Allocation (LDA) analysis and reinforcing the hypotheses through K-means clustering and Principal Component Analysis (PCA).

3.3.1. TF-IDF

Term frequency inverse document frequency (*tf-idf*) was used to identify the most relevant terms. It refers to the importance of a term within a corpus of documents based on the equation

$$idf(\text{term}) = ln\left(\frac{n_{documents}}{n_{documents\ containing\ term}}\right)$$

to measure the weight of a word by its collocation. Commonly used words appearing in all collections are scored with low values, and those that are used less overall are highly scored. Therefore, they are adjusted in a compound by combining the multiples of frequency and rarity of the terms in descending order. This procedure also yields a median utilized in establishing the minimum accepted frequency probability per document. This aids in determining the sparsity threshold for computing the quantity of terms to be excluded from the corpus. Put simply, following the computation of *tf-idf* scores, we also compute the *tf-idf* median for the entire corpus of documents, which in turn assists in pinpointing the minimum accepted frequency probability.

3.3.2. Latent Dirichlet Allocation Analysis

LDA is a probabilistic model widely used in text analysis for topic modelling. LDA assumes that documents are mixtures of topics and topics are mixtures of words (Blei *et al.*, 2003). It employs Dirichlet distributions to represent these mixtures, with Dirichlet parameters (α) influencing the distribution characteristics and the discovery of topics (Wallach *et al.*, 2009). This machine learning technique does not require a predefined dictionary or interpretative rules for identifying latent clusters of co-occurring words in a collection (Hannigan *et al.*, 2019). Instead, it establishes correlations between words within documents, and treats them as topics of interest.

The LDA model is described by the equation: $\theta_j \sim D[\alpha]$, $\phi_k \sim D[\beta]$, $z_{ij} \sim \theta_j$, $x_{ij} \sim \phi_{zij}$, where α and β are the prior Dirichlet parameters automatically computed via a statistical Dirichlet distribution (Newman *et al.*, 2009). θ_j represents the topic distribution for document j, φ_k signifies the word distribution for topic k, z_{ij} denotes the topic for the ith word in document j, and x_{ij} indicates a specific word (Blei *et al.*, 2003). The machine learning algorithm computes suitable Dirichlet prior distributions α and β based on the data using the *Topicmodels package v0.2-12* in R (Grün *et al.*, 2021). The key outputs derived from LDA include the extracted topics, their constituent keywords ranked by probability, gamma (γ) values quantifying overall topic popularity, and theta (θ) values representing topic prevalence in specific documents.

3.3.3. Gibbs sampling

This study applied the generative Gibbs sampling method, a validated Markov Chain Monte Carlo (MCMC) technique (Mimno *et al.*, 2008). It iteratively estimated latent topics within documents while determining the statistically optimal number of topics (k). To mitigate human bias, a comprehensive set of four metrics was utilized (Arun *et al.*, 2010; Cao *et al.*, 2009; Deveaud *et al.*, 2014; Griffiths & Steyvers, 2004). Building upon LDA, the unsupervised Gibbs method (Mimno *et al.*, 2008) probabilistically identifies the optimal k value, processes local data, and maps term co-occurrences across documents and topics. The machine deductive algorithm, utilizing the R package Topicmodels 0.2-12 (Hornik & Grün, 2011), ensures an automated statistical approach.

3.3.4. K-means clustering

These initial parameterization of these LDA topics involved cluster analysis using the k-means algorithm. Additional statistical validation was achieved through an additional cluster analysis conducted using *the KablExtra 1.3.4* and *DoParallel 1.0.17* libraries in R Studio (Daniel *et al.*, 2022; Zhu *et al.*, 2021). This approach offered enhanced comprehension of topic distribution within the document collection. The cluster analysis aimed to provide a deeper understanding of how topics were distributed across the collection of documents under study. This step enhances the researchers' understanding of distribution patterns and relationships among the identified topics, contributing to the overall robustness of the analysis. The works of Zhu *et al.* (2021) and Daniel *et al.* (2022) served as key references and resources for implementing this statistical validation approach.

3.3.5. Principal Component Analysis

PCA was conducted to quantitatively validate hypotheses derived from LDA topics. PCA utilizes eigenvalue decomposition, effectively reducing multidimensional data into principal components (Jolliffe, 2002). The LDA topics, parameterized through a cluster analysis using the k-means algorithm, were subjected to PCA to identify relationships among topic dimensions, based on the proximity of eigenvectors and eigenvalues (Abdi & Williams, 2010). The fraction of the total variance explained by each dimension effectively highlighted the core topics. This analytical shift from exploratory LDA to confirmatory PCA empowered the statistical validation of hypothesized relationships, relying on the outcome of PCA for topic correlations rather than solely on the qualitative LDA results. Further statistical validation was achieved through an additional cluster analysis conducted using the *KablExtra 1.3.4* and *DoParallel 1.0.17* libraries in R Studio (Daniel *et al.*, 2022; Zhu *et al.*, 2021), enhancing comprehension of topic distribution within the document collection. Simultaneously, PCA was applied, considering the probability of observations appearing in each cluster (topic), and subsequently dimensionally reduced it to calculate topic variance based on eigenvalues. The reduction of dimensions and cross-validation of identified topics were executed using the k-means algorithm parameterized by the machine (Chan *et al.*, 2013).

3.4. Pre-processing

The pre-processing protocol comprised seven steps, as depicted in Figure 2. This process included:

1. Translating all texts into English using the TranslateR 1.0 package (Lucas & Tingley, 2015). While most observations were already in English, translation ensured full English readability, with results reviewed by the authors to enhance reliability.
2. Creating a corpus containing all texts about the host, utilizing the Pdftools 3.3.0 and TM 0.7-8 libraries in R Studio (Feinerer, 2015; Ooms, 2022). The "about the host" variable was transformed into a unified full corpus.
3. Performing a preliminary cleansing process to eliminate non-contributory words for topic formation. This included encoding the corpus in a UTF-8 pattern, converting words to lowercase to prevent errors in detecting special characters, removing stop words (e.g., "the," "is," "and," "for," "can"), as well as eliminating numbers, whitespaces and punctuation.
4. Carrying out the second phase of the cleansing process, where recurring non-representative terms, persisting in the corpus after the initial cleansing, were removed using an algorithm.
5. Implementing stem processing to retain only the word stems, thus replacing words with the same meaning and plurals. This prevents bias through double calculations in statistical inferences. The algorithm identifies and retains only the core of the words. As for instance, it keeps only the "experi" from "experience" and "experiences", counting them as the same term. It enriches topic modelling and avoids bias through double calculations in statistical inferences.
6. Applying term frequency inverse document frequency (*tf-idf*).
7. Applying the determined median (0.16975) from the *tf-idf* model to the corpus, as referenced in Table 1, to establish the minimum accepted frequency probability per document. This contributed to defining the sparsity value (<0.983%) to determine the number of terms to omit from the research. Consequently, nine observations were excluded, as they did not contain any of the identified *tf-idf* terms, resulting in 1164 remaining observations. The most frequently used terms are presented in Figure 3.

Table 1
Summary of *tf-idf* to define sparsity and terms to omit

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.03158	0.13447	0.16975	0.19598	0.21670	4.07395

Source: Own elaboration.

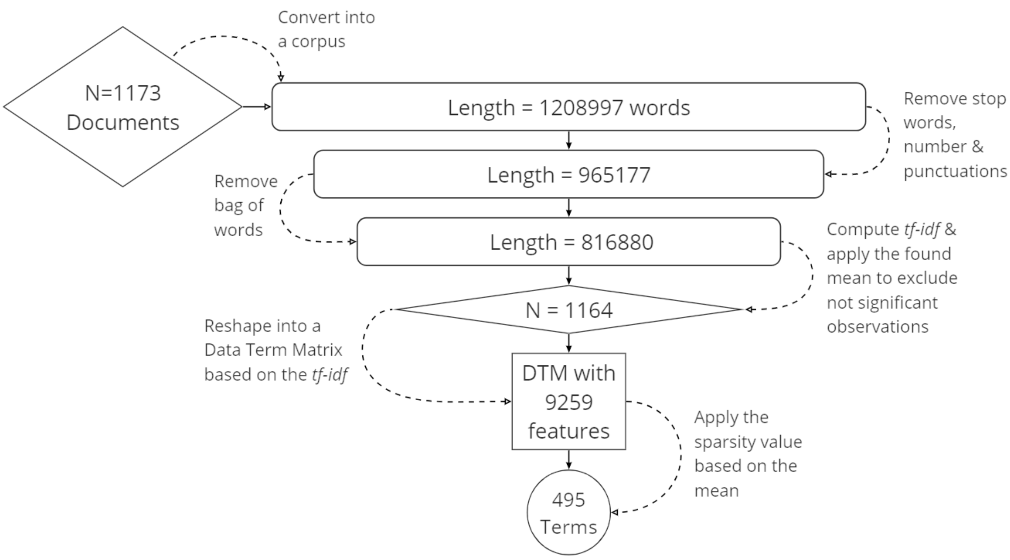

Figure 2
Protocol modelled for pre-processing step
Source: Own elaboration.

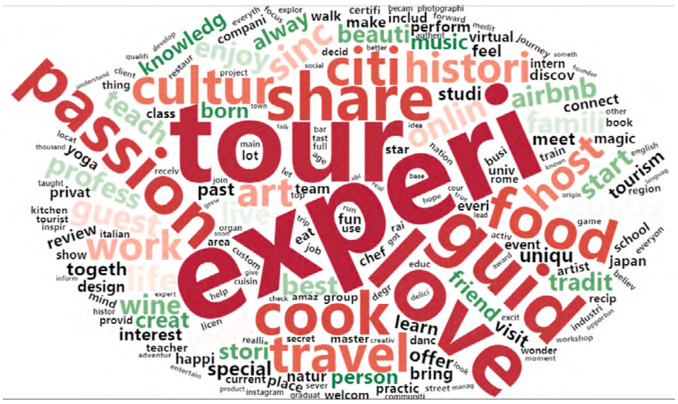

Figure 3
Word cloud with the most frequent terms
Source: Own elaboration.

This is particularly valuable in fields like statistics, machine learning, and simulations, where replicating experiments or analyses is essential for validation and comparison.

Four metrics were considered (Arun *et al.*, 2010; Cao *et al.*, 2009; Deveaud *et al.*, 2014; Griffiths & Steyvers, 2004) to provide insights into the number of topics required. *CaoJuan2009* and *Deveaud2014* metrics exhibited consistent decreases in values as the number of topics decreased, indicating improved topic coherence and distinctiveness. In contrast, *Griffiths2004* shows an ascending trend, suggesting a better model fit with fewer topics. Most notably, *Arun2010* displayed a substantial increase in value as the number of topics decreased, reflecting enhanced topic interpretability.

Figure 4 reveals a range of latent topics from 4 to 12. However, a closer examination of Figure 5 confirmed the presence of six statistically significant latent topics. This robust statistical evidence supports the choice of six topics as the optimal configuration for topic modelling analysis. The selection is influenced by contextual factors, the corpus size, which encompasses 495 features, and the dataset's nature, which comprises 1164 individual observations (Lakshminarayanan & Raich, 2011; Mimno *et al.*, 2008). This decision harmoniously aligns with our dataset's unique characteristics, ensuring that the resulting topics are not only statistically sound but also contextually relevant to our research domain. These findings collectively validate the selection of six topics, striking a balance between quantitative metrics and meaningful topic interpretation in alignment with research objectives and dataset characteristics.

4. Data Analysis

4.1. Topic modelling

The Gibbs method was initially applied before LDA to determine the statistically optimal number of topics (K) emerging from the document corpus. To ensure reproducibility, a fixed seed of 77 was chosen, which guarantees consistent results each time random numbers are generated. A fixed seed asserts the same results every time that random numbers are generated.

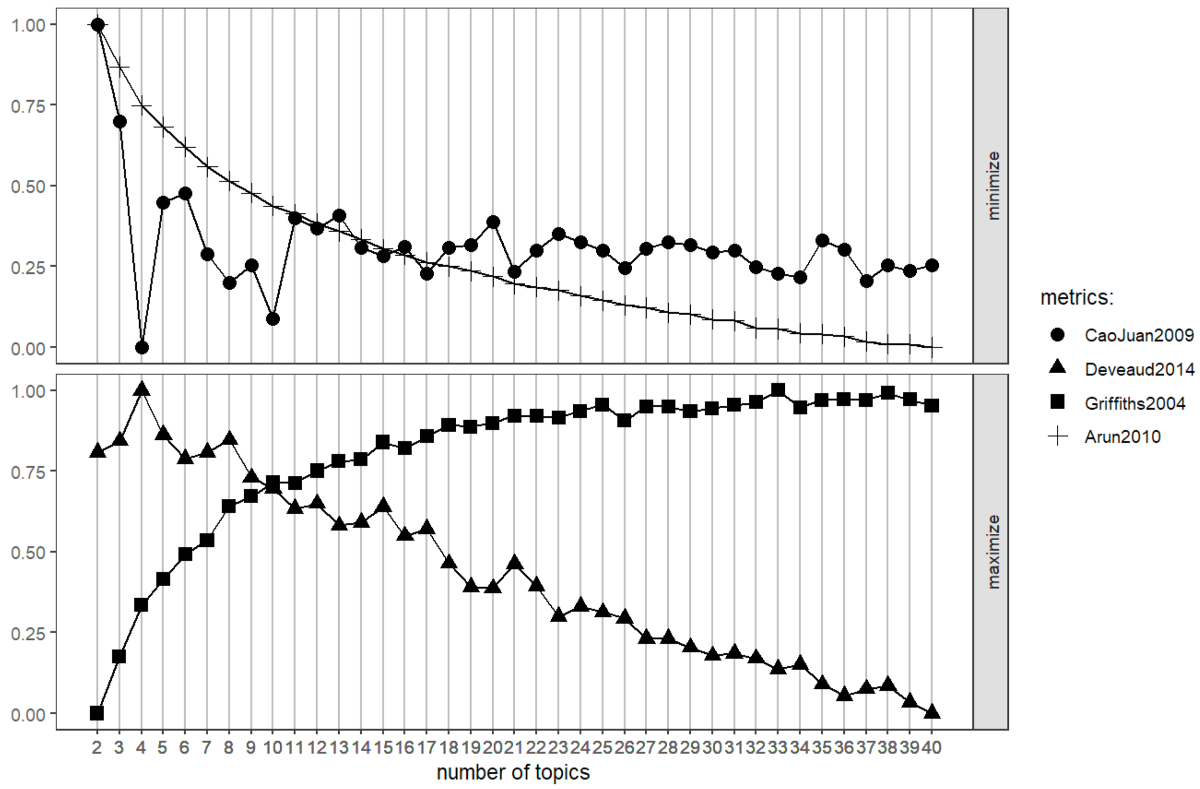

Figure 4
Topic-probability visualization
Source: Own elaboration.

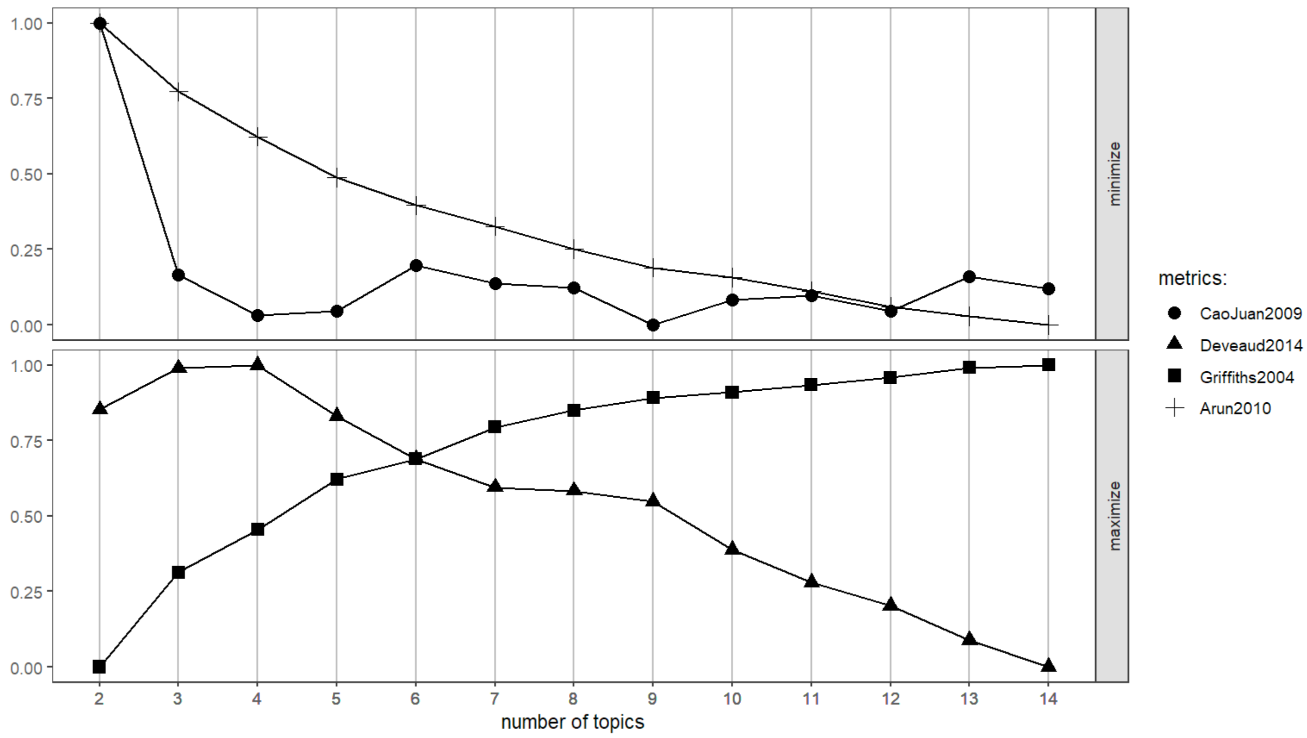

Figure 5
Topic-probability dendrogram
Source: Own elaboration.

The (k) value based on the outcome of the Gibbs sampling procedure was used to access the data, as shown in Figure 6, using LDA to capture substantial inter-intra structures of the data (Sagadevan *et al.*, 2022). As mentioned above, the seed number of 1961 was also set to the LDA to ensure reproducibility.

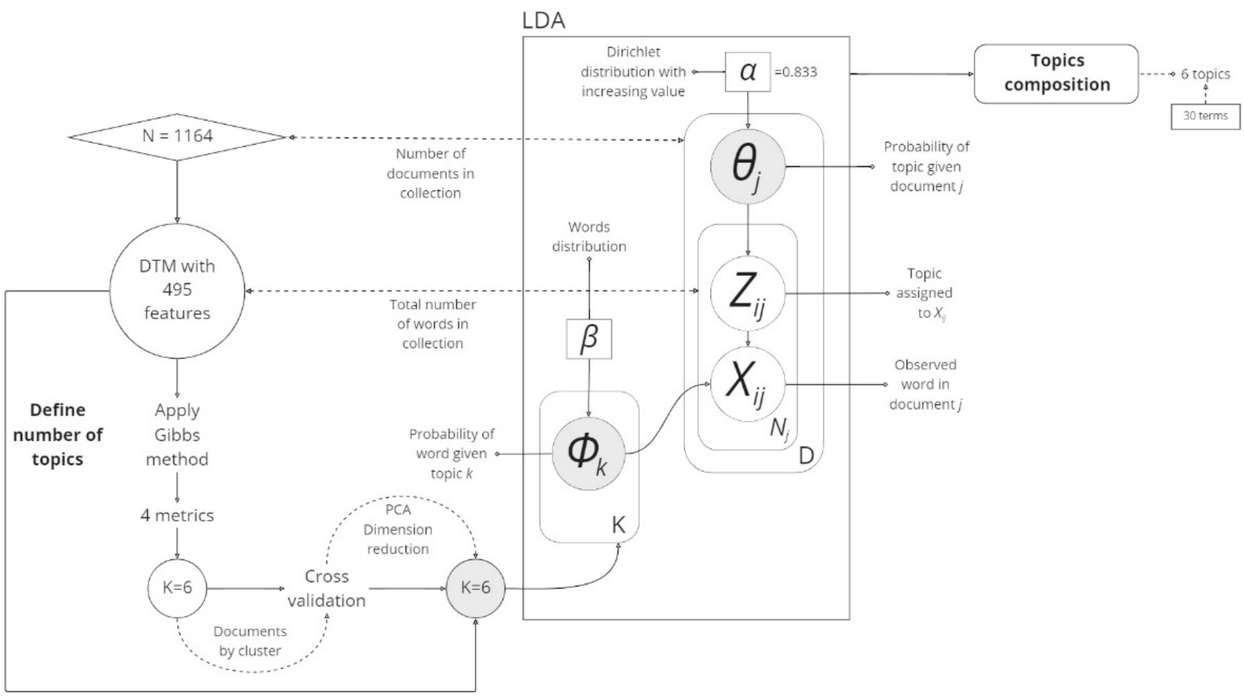

Figure 6
Protocol model for topic-modelling steps
Source: Own elaboration.

Alpha (α) and beta (β) hyperparameters, governing topic-document and topic-word distributions respectively, were not predefined but algorithmically inferred by the model to tailor Dirichlet prior to the data. The model estimated an alpha value of 0.833, indicating uniform topic mixtures among the documents. This automated approach ensured parameters tailored to the data without imposing strong preconceived assumptions (Wallach *et al.*, 2009). The authors prioritized the statistical correlation identifications by machine before conducting contextual inductive analysis.

A total of 500 iterations were employed with a burn-in of 0 iterations to achieve model convergence. This optimal number of iterations assured a stable state, and converges the model throughout its execution. Following best practices (Blei *et al.*, 2003; Lakshminarayanan & Raich, 2011), the log-likelihood value that quantifies the model's fit to the data, stabilized at –215963.3. This stabilization indicates that our LDA model had reached a relatively stable state in terms of performance. Additionally, perplexity, a metric used to assess model quality, was calculated to be 351.6628, which also suggests that the model provided a satisfactory representation of the data, as shown in Figure 7.

Beta weights were estimated using automated procedures as a 6 × 532 matrix representing the word distributions for each topic. The machine-generated weights provided an objective statistical foundation for understanding the topic-word relationships prior to being accessed by the authors for inductive analysis. This data-driven approach increases the robustness of merging automated statistical outputs with human interpretative processes to interpret and contextualize topics on behalf of the research goals.

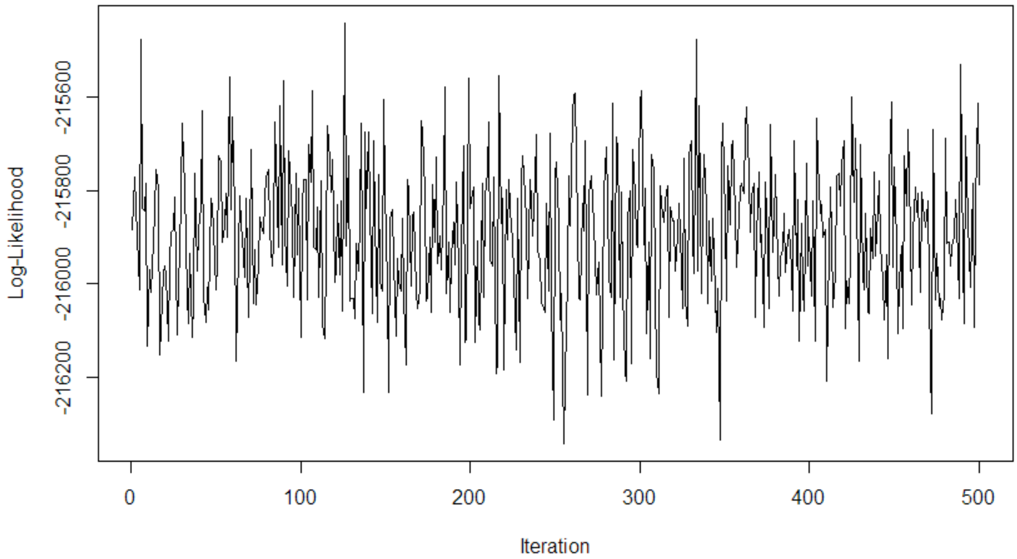

Figure 7
Log-Likelihood Convergence Plot
Source: Own elaboration.

4.1.1. Topic model analysis

After setting the optimal number of six latent topics, LDA identified the words to compose each topic through the assigned probabilities, ranking them in decreasing order to determine their influence on the topic's meaning. The authors considered the keywords with the highest probability in each specific topic based on their theta value, accounting for the model's admixture approach allowing a word to belong to different topics. Furthermore, the algorithm specified the gamma value of each topic to gauge its relevance to the model.

Following automated extraction, the authors proceeded with the interpretative phase, conducting a qualitative analysis to make sense of the topics and their respective word lists according to the observations they were related to. The interpretation involved relating the terms to the broader context of our research objectives and existing knowledge. This process allowed the calibration of topics and align with the study's nuances.

Before starting the labeling process, the corpus containing all texts was reverted to its initial format of individual observations using the Quanteda R package. This library, designed for quantitative textual data analysis, facilitated the transformation of the table back to its original form, including new columns for variables: topic number, label, keywords, and gamma values. This approach increased the reliability of interpreting topic meanings in the contextual inductive analysis, as it exposed the authors to the top-30 terms of each topic and the most relevant statistically assigned observations (Benoit *et al.*, 2018), as seen in Table 2, Figure 8, and Figure 9. This procedure mitigates bias and guides the researchers' work (Maier *et al.*, 2018). Additionally, a statistical approach considering the top-10 words and their probability scores complemented the authors' qualitative interpretation in naming the topics through thorough analysis.

Table 2
Topics, keywords, gamma, and referred observations

Topic number	Label by beta	Top 30 keywords	Gamma	N Obs.	Related Obs.
1	Experi love sinc best enjoy profess connect	Experi, love, sinc, best, enjoy, profess, connect, happi, virtual, person, start, rome, guest, decid, job, focus, design, realli everyone, got, activ, alway, italian, moment, tourism, communit, real, ever, offer, opportun.	0.1692834	135	523, 710, 775, 798, 887
2	Passion share love cultur countri friend born	Passion, share, love, cultur, countri, friend, born, live, special, uniqu, meet, stori, discov, lot, rai, region, tourism, local, thing, amaz, wonder, everyth, secret, work, qualifi, expert, hope, goal, give, main.	0.1680775	173	62, 986, 244, 864, 172
3	Work creat knowledge team wine event includ	Work, wine, creat, knowledg, team, event, includ, natur, compani, univ, experi, live, intern, profess, busi, degr, industry, show, educ, top, tast, nation, organ, bar, excit, award, photographi, workshop, entertain, creativ.	0.1668134	185	103, 114, 118, 230, 233
4	Experi famili cook food host onlin airbnb	Experi, cook, food, host, onlin, famili, airbnb, guest, tradit, togeth, start, review, eat, japan, learn, class, star, chef, past, recip, kitchen, welcom, cuisin, restaur, delici, instagram, authent, bring, grew, bake.	0.1661938	225	24, 31, 42, 222, 332
5	Tour guid histori citi travel beauti local	Tour, guid, travel, cit, histor, beaut, local, visit, interest, feel, place, privat, alway, group, area, walk, custom, licen, tourist, offer, let, trip, english, explor, histor, look, town, museum, plea, everi.	0.1657290	219	9, 107, 659, 700, 825
6	Art, life, teach, practic, music, studi, perform,	Art, life, teach, music, studi, perform, yoga, practic, artist, school, mind, teacher, master, danc, magic, train, certif, game, inspir, believ, current, age, use, journey, medit, client, taught, combin, heal, techniqu.	0.1639029	227	60, 71, 205, 284, 291

Source: Own elaboration.

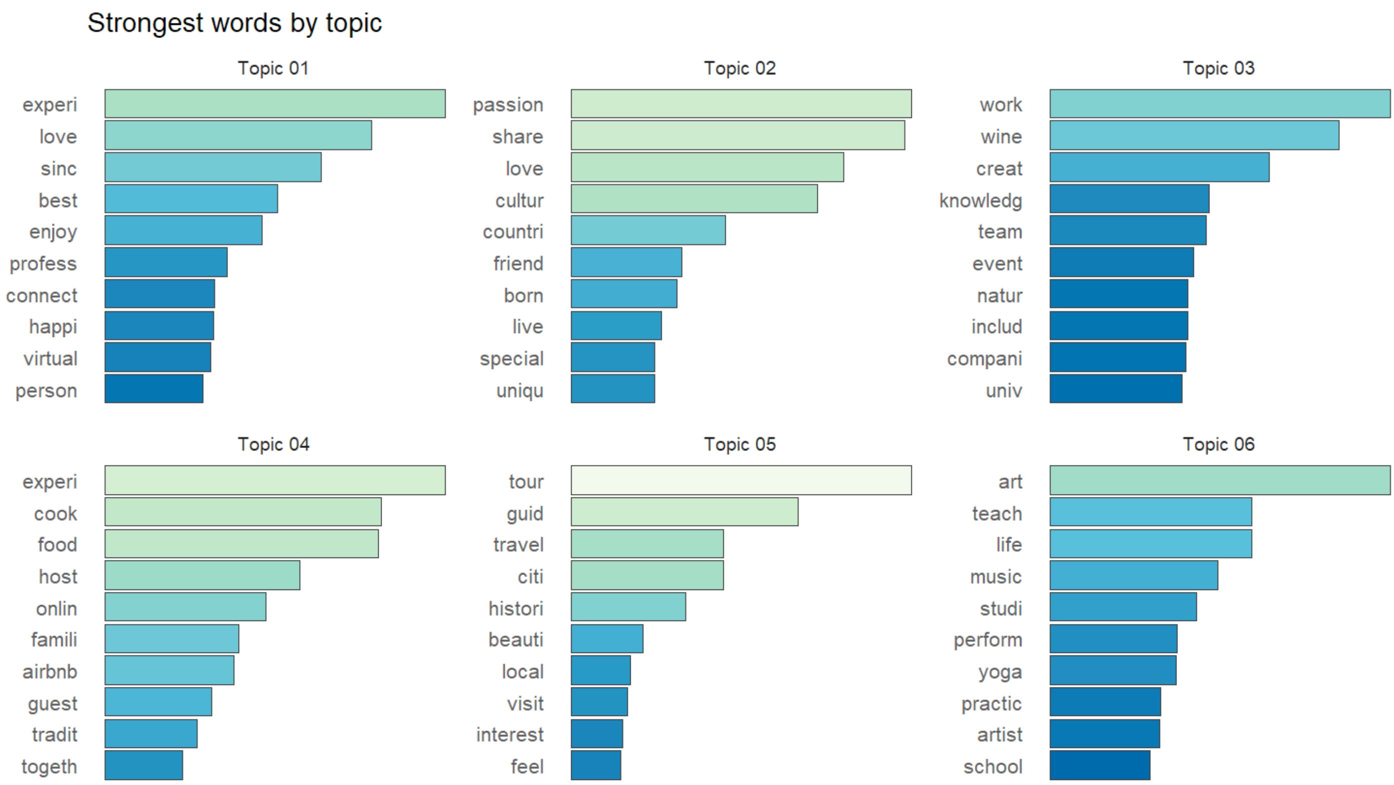

Figure 8
Strongest keywords by topic
Source: Own elaboration.

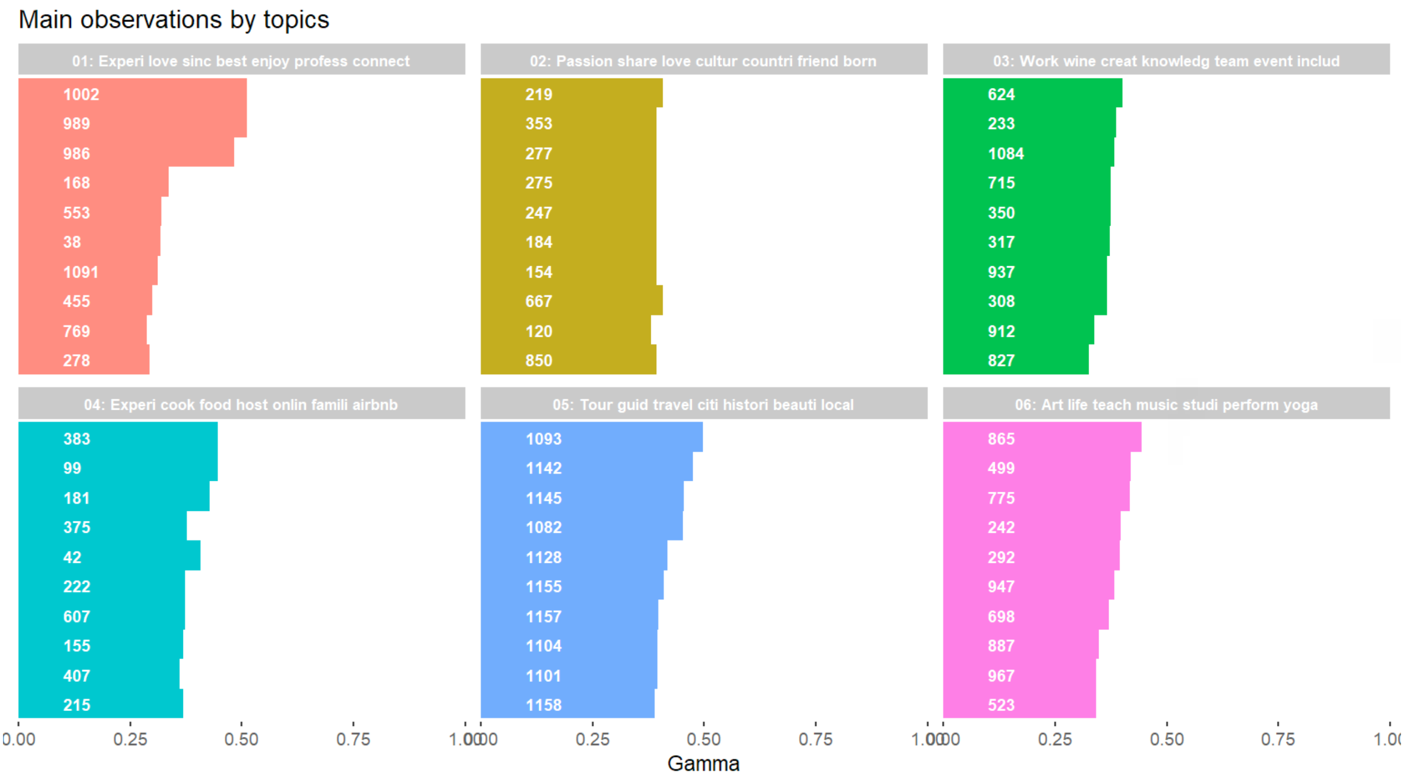

Figure 9
Main observations by topic
Source: Own elaboration.

4.1.2. Topic model per descriptive statistics and control variables

The R function GenderizeR 0.6.0 was additionally employed to determine the gender of GWs, serving as a control variable. This library uses a localized database from various countries to conduct a statistical analysis, accurately assigning gender based on (Santamaría & Mihaljević, 2018; Wais, 2016). The researchers randomly reviewed the results, and all of them had a certainty score no less than 0.75 – from 0 to 1. In addition to gender, two other nominal variables were also recorded: "couple," indicating products developed by two individuals on the GE platform; and "group," denoting cases where more than two individuals offered the gig (see Table 3).

Furthermore, the innovation feature was calculated by considering the date frame variable. GWs with a profile on GE platforms before March 2020 or those offering multiple experiences were assigned a value of 1; otherwise, 0. The aforementioned procedure resulted in a new CSV file comprising 1164 observations and eight variables, including innovation, topic number, and gender (see Table 3, 4 and 5).

Table 3
Descriptive statistics of the data by gender and other nominal groups

Gender	Topics												Total	
	T1		T2		T3		T4		T5		T6			
	#	%	#	%	#	%	#	%	#	%	#	%	#	%
Men	38	3.3	91	7.8	64	5.5	87	7.5	70	6.0	126	10.8	476	40.9
Women	75	6.4	144	12.4	94	8.1	86	7.4	76	6.5	151	13.0	626	53.8
Couple	2	0.2	0	0.0	11	0.9	6	0.5	25	2.1	15	1.3	59	5.1
Group	0	0.0	1	0.1	0	0.0	0	0.0	1	0.1	1	0.1	3	0.3
Total	115	9.9	236	20.3	169	14.5	179	15.4	172	14.8	293	25.2	1164	100.0

Source: Own elaboration.

Table 4
Descriptive statistics of the data by innovation variable

Innovate	Topics												Total	
	T1		T2		T3		T4		T5		T6			
	#	%	#	%	#	%	#	%	#	%	#	%	#	%
No	11	0.9	23	2.0	11	0.9	18	1.5	31	2.7	52	4.5	146	12.5
Yes	104	8.9	213	18.3	158	13.6	161	13.8	141	12.1	241	20.7	1018	87.5
Total	115	9.9	236	20.3	169	14.5	179	15.4	172	14.8	293	25.2	1164	100.0

Source: Own elaboration.

Table 5
Descriptive statistics of the innovation variable by gender

Innovated	Gender								Total	
	Men		Women		Couple		Group			
	#	%	#	%	#	%	#	%	#	%
No	58	5.0	80	6.9	8	0.7	0	0.0	146	12.5
Yes	418	35.9	546	46.9	51	4.4	3	0.3	1018	87.5
Total	476	40.9	626	53.8	59	5.1	3	0.3	1164	100.0

Source: Own elaboration.

4.2. Clustering and PCA

A cluster analysis was conducted to provide statistical validation through visualization using the KablExtra 1.3.4 and DoParallel 1.0.17 libraries in R Studio (Daniel *et al.*, 2022; Zhu *et al.*, 2021). It enhances the comprehension of topic distribution across the various documents in the collection. Additionally, PCA was performed. It considered the probability of observations appearing in each cluster (topic) by analysis of Theta and Gamma value correlations before dimensionally reducing it to calculate the topic variance based on its eigenvalues. The machine parameterized *k-means* was used for cross-validation of the identified topics and dimensionality reduction (Chan *et al.*, 2013).

To augment the depth and rigor of the analysis, the researchers employed PCA as a complementary method to LDA. While LDA offers insights into term-topic-document relationships and latent topics, it is essentially exploratory. In contrast, PCA, known for its confirmatory nature, quantifies these relationships, contributing to hypothesis validation through exploratory visualization (Jollife & Cadima, 2016; Ogunleye *et al.*, 2023). The application of PCA to LDA topics rigorously confirmed the extent to which these topics relate to the research questions, significantly enhancing the credibility and validity of the findings (Inoue *et al.*, 2023). This strategic blend of statistical exploratory and confirmatory analyses strengthens the study's robustness (Sosianika *et al.*, 2018; Koyuncu & Kılıç, 2019; Shahrakipour, 2021).

The percentage of variance in Table 6 reveals the core of the six topics, facilitating further analysis. The visualized proximity between dimensions helped confirm the topics' meanings by associating them and analyzing the proximity of centroids, thus establishing their relevance. Hypotheses H4 and H5 are confirmed as RQ2 is addressed based on the proximity of the dimension's core.

Table 6
PCA's summary

Dimensions	Eigenvalue	Variance %	Cumulative Variance %
Dim.1	1.6	25.9	25.9
Dim.2	1.4	22.7	48.6
Dim.3	1.2	19.3	67.9
Dim.4	1.0	17.4	85.3
Dim.5	0.9	14.7	100.0
Dim.6	0.0	0.0	100.0

Source: Own elaboration.

5. Results

5.1. Topic model findings

After applying the aforementioned protocol, as depicted in Figure 6, to answer RQ1, the topics were labeled as follows: Topic one (T1) was designed as "professional experience," reflecting the GW's intention to further develop themselves through professional experience. It conveys the perceived opportunity to act focused on their offered gig to activate and connect with their guest (user) in a real and enjoyable way; Topic two (T2) was titled "passion for sharing," signifying GW's joy in sharing their expertise with clients; Topic three (T3) was named "knowledge through creative work and education," linked to educational experiences through business or scholarly paths, involving relations that contribute to acquiring knowledge. Topic four (T4) is tagged as "classic traditional experience." It is associated with the experience acquired through familiar or community learning of GWs. They are focused on authenticity and specialized in the field of their offers. Topic five (T5) relates to the "GW's interest in showing their feelings," reflecting the GW's interest in showcasing the places they guide. There is a demonstration of pleasure in offering their look at the town, exploring historical places with a singular view. Topic six (T6) was labelled "well-being experience," emphasizing the GW's aim to inspire users with mastered experiences.

5.1.1. Descriptive statistics and control variables

Table 3 illustrates a balanced gender distribution within the sample, with a higher percentage of women (53,8%). The majority of participants engaged in innovation through GE platforms (87.5%), as shown in Table 4. Women accounted for 46.9% of the innovators in the sample, whole products offered in groups were the least representative (0.3%) (Table 5). Additionally, as shown in Table 3, T6 and T2 emerged as the most prominent topics within the sample (25.2% and 20.3%, respectively) and were particularly representative within the women's population (13% and 12.4%, respectively). Despite T1 having the highest gamma value (based on the frequency and inverse frequency) (*Table 2*), it was not the topic with the most frequently used words by individuals in the sample. Furthermore, the population with a passion for sharing (T2) and well-being experience (T6) exhibited the highest number of identified innovators.

5.1.1. Topics and Hypotheses

To address RQ2, the authors examined topic formation and associations. T1 and T2 confirm H1, as the terms found in both topics were associated with the passion that motivates GWs when offering their gigs and products on GE platforms.

H2 received confirmation from T1, T3, and T4, indicating that the interaction between GWs and GE platforms contributes to their entrepreneurial learning curve and personal development. Based on previous or actual interactions, the relationships among peers through these platforms contribute to personal and professional development and support an increase in SEE.

T3 corroborated H3 by revealing that internalizing knowledge is influenced by previous learning experiences through educational or professional interactions and is amplified through relationships between peers on GE platforms to achieve business value. This corroborates the assumption that, when involved with entrepreneurial activities, GWs are prone to increase their SEK supporting increased SEK.

5.2. Confirming results with PCA

As seen in Figure 10, PCA confirmed six nodes with high proximity between four of them. Node one and two, corresponding to T1 and T2, supported the validation of H4, emphasizing the relationship between SEE and GWs motivated by passion. On the other hand, dimensions three and four, T3 and T4, respectively, slightly overlap dimension two, but the central nodes of their centroids are quite different. However, H4 is validated due to the distance between the cores of the centroids, which is mainly influenced by nodes one and two.

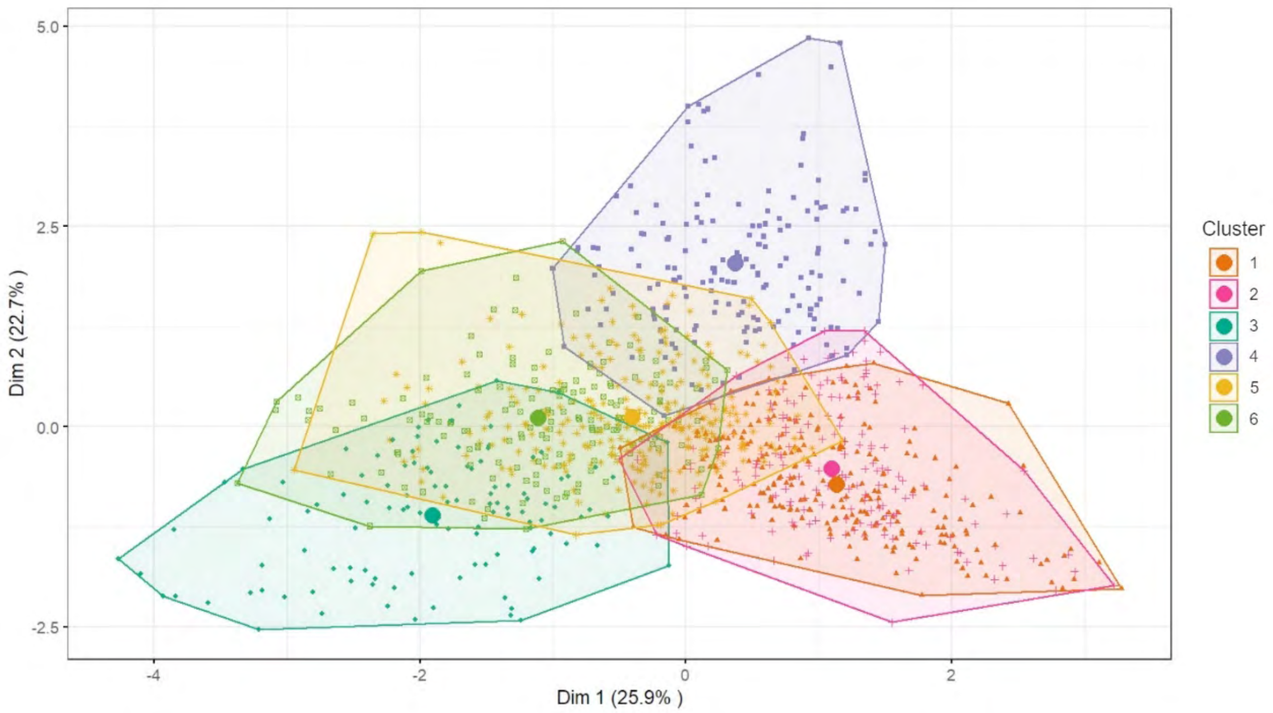

Figure 10
Observation distribution by the six identified dimensions

Node three, T3, does not contribute to confirm H5. Its distance from node two, even with some overlapping, is large, which leads to the assumption that SEK is not correlated with the GWs passion. Nevertheless, nodes five and six, T5 and T6, present a significant proximity and overlap between them, and are very close to node three, which will be discussed further. Table 7 summarizes the results of this study.

5.2. Passion through proximity of the topics

To respond to RQ3 all previous findings were considered. Therefore, passion for growth was found through the analysis of the close core relationship between T1 and T2 and the probabilistic proximity with T6 (Figure 10). Moreover, Table 4 shows that T1, T2, and T6 represent 47.9% of the ones that innovated. This assumption was made because of the search for development associated with the persistence of keeping their businesses on the platforms, even if reformulation of the products was required. From this perspective, passion for products/services and passion for inventing was confirmed.

Passion for people is found in the core proximity between T5 and T6, and T2 connects through some vertices, as shown in Figure 10. Therefore, 60.3% of the players share their products motivated by the passion they have for connecting with people through experiences, which is the main explanation for this source of passion. Furthermore, aggregating the association with T4 confirms passion for a social mission. They represent 75.7% of the sample, motivated by their will to connect with people, community, and share experiences at the same time, impacting their perceptions of their culture, society, and behaviors. Their intent is to create or consolidate a positive perception of their community or the culture they are part of. Passion for competition was not confirmed.

Table 7
Summary of results

Research questions	Hypothesis #	Synopsis of hypotheses	Topics	Findings
RQ1		Motivating factors	6	T1 - Experience cumulation T2 - Passion sharing T3 - Knowledge and creativity T4 - Classic traditional experience T5 - Feeling community local T6 - Well-being experience
RQ2	H1	GE relates with PA	T1 and T2	Supported
	H2	GE relates with EE	T1, T3 and T4	Supported
	H3	GE relates with EK	T3	Supported
	H4	EE relates with PA	T1 and T2	Partially supported
	H5	EK relates with PA	Not	Rejected
RQ3		Sources of passion	5	Passion for growth; Passion for people; Passion for product/services; Passion for innovation; Passion for social mission.

Source: Own elaboration.

6. Discussion

This research contributes to the understanding of passion and self-efficacy as key motivators for entrepreneurship among GWs on GE digital platforms. It reveals that passion, self-efficacy through experience, and knowledge drive GWs to venture into entrepreneurship. The study involved a two-step process, beginning with LDA topic modeling of 1164 observations from GWs' profiles to unveil their motivations for offering products on GE platforms. Six topics were identified, with two confirming the importance of passion for business activities on GE platforms. This highlights the role of passion as a determinant in entrepreneurial orientation or intention beyond a narrow entrepreneurship-focused approach.

Moreover, the study found that self-efficacy through experience and knowledge motivates GWs to engage with GE platforms as an initial step toward entrepreneurship, increasing their perception of self-control. The strong association between topics related to sharing life experiences and accumulated knowledge underscores the value of self-awareness and locus of control in entrepreneurial endeavors.

Second, further analysis using PCA reveals that while passion is closely linked to self-efficacy through experience, it has a weaker connection with self-efficacy through knowledge. This suggests that passion's influence on offering services on GE platforms is primarily driven by the desire to gain experience, rather than knowledge, which requires emotional involvement.

Third, two distinct groups emerged based on core proximity analysis. The first group, composed of T1 and T2, reflects GWs who engage with GE platforms not solely for business but out of genuine affection. They derive passion and satisfaction from their work, drawing on past experiences or pursuing new ones. The second group, encompassing T5 and T6, is motivated by an inner sense of well-being and a desire to share personal appraisals about places, objects, or activities. The convergence of these groups highlights GWs with a heightened inclination for innovation.

Incorporating T4, which reveals an intent to impact the community and preserve local social and cultural traditions, nearly all passion sources are represented, aligning with Cardon *et al.'s* (2017) findings. The exception is passion for competition, which remains elusive due to limited control imposed by GE platforms. These platforms offer a range of features, but control is vested in algorithms determining which results occupy the top tier of the page.

Although GWs can enhance their services, innovate technically, and leverage positive reviews to expand their reach, full comprehension of the platforms' underlying artificial intelligence (AI) remains obscured. This underscores existing literature highlighting policy and AI implications that restrict entrepreneurs from exercising complete control over their businesses.

T3 is conspicuous for not aligning with established passion sources. Neither automated statistical analysis of keywords and observations nor authors' visual assessments reveal a connection to any known passion source. This suggests that T3 may represent an undiscovered passion source arising from this study. While it typically derives from other factors or goals, like experience transfer (Geissinger *et al.*, 2019), it might signify a novel source: a passion for knowledge. Moreover, the proximity between T3 and T2 implies that Self-Efficacy through Knowledge (SEK) accumulates from Self-Efficacy through Experience (SEE), contributing to the understanding of GE platforms as an urgent entrepreneurial ecosystem, impacting entrepreneurial intention through self-efficacy accumulation.

The findings further endorse existing literature suggesting that GE platforms empower women in entrepreneurship (Md Isa *et al.*, 2020; Silva & Moreira, 2022). The sample reveals that women offer a higher number of products than men and exhibit greater innovation in leveraging GE platforms for their entrepreneurial activities. They have pioneered novel approaches to selling their services online, demonstrating heightened sensitivity to identifying opportunities and a strong sense of alertness. Hence, it can be argued that this outcome is associated with women's greater pursuit of passion and well-being when engaging with GE platforms for entrepreneurial endeavors. This is substantiated by the larger percentage of women displaying passion for growth, people, products, innovation and social mission.

Lastly, GWs with pre-existing relationships with GE platforms demonstrate a keen awareness of business opportunities and are more adept at developing new services within the ecosystem, drawing on their prior experiences. In conjunction with topics related to the impact and well-being of GWs' communities, it is reasonable to assert that GE platforms are fostering a sustainable entrepreneurial environment. By mitigating risk, fostering innovation, and alleviating resource constraints, GE platforms dismantle barriers to the development of entrepreneurial ideas that extend beyond mere profit.

7. Conclusion

This investigation has several practical implications, reinforcing established theories. First, GWs display high levels of entrepreneurial alertness and tend adopt GE platform's innovation strategy. Their motivation stems from passion and self-efficacy for their products, lowering barriers related to resources and social capital, reducing entry risk of GWs and fostering a fair entrepreneurial ecosystem. This suggests that GWs, driven by passion, prioritize well-being over pure profit.

This study aligns with existing theories on entrepreneurs' sources of passion, confirming Cardon *et al.'s* (2017) framework. The innovative methods employed, such as LDA to mitigate topic modeling bias and inductive statistical inferences, expand the understanding of the phenomenological approach. The research protocol, emphasizing efficiency in data access, preprocessing, and analysis using R packages, contributes to knowledge building. While the study covered data from the initial three GE platforms, further research could explore additional platforms with different business activities.

Though the study did not confirm passion for competition as a motivation factor, it underscored the significance of knowledge and well-being. Consequently, further research is needed to explore this phenomenon from a different angle. Lastly, researchers may apply similar methods to different populations, such as students, or employ alternative research approaches to solidify the importance of passion, extending beyond early-stage entrepreneurship on GE platforms.

This investigation presents certain limitations, including its focus on data from the only three GE platforms innovating on online tourism experiences at the time, which may limit its generalizability to other platforms due to their unique purposes and dynamics. The study's collective analysis of GWs without demographic granularity suggests a need for a more detailed approach to understanding their particularities. The evolving GE platforms highlight the importance of considering temporal factors and their influence on motivations and strategies, necessitating longitudinal studies. The method employed in this investigation is novel and requires further exploration and refinement, prompting new research to adopt its principles and integrate different databases and metrics. Lastly, the correlation between innovation and GE platforms demands a more comprehensive investigation.

8. Acknowledgments

This work was financially supported by the Research Unit on Governance, Competitiveness and Public Policies (UIDB/04058/2020), funded by national funds through FCT – Fundação para a Ciência e a Tecnologia.

9. References

Abdi, H., & Williams, L. J. (2010). Principal component analysis. *Wiley Interdisciplinary Reviews: Computational Statistics*, *2*(4), 433-459. https://doi.org/10.1002/wics.101

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of Applied Social Psychology*, *32*(4), 665-683. https://doi.org/10.1111/j.1559-1816.2002.tb00236.x

Ali, A., & Yousuf, S. (2019). Social capital and entrepreneurial intention: Empirical evidence from rural community of Pakistan. *Journal of Global Entrepreneurship Research*, *9*, 64. https://doi.org/10.1186/s40497-019-0193-z

Allon, G., Cohen, M., & Sinchaisri, P. (2023). The impact of behavioral and economic drivers on gig economy workers. *Manufacturing & Service Operations Management*, *25*(4), 1376-1393. https://doi.10.1287/msom.2023.1191

Anwar, S. T. (2018). Growing global in the sharing economy: Lessons from Uber and Airbnb. *Global Business and Organizational Excellence*, *37*(6), 59-68. https://doi.org/10.1002/joe.21890

Arun, R., Suresh, V., Madhavan, C. E. V., & Murty, M. N. (2010). On finding the natural number of topics with Latent Dirichlet Allocation: Some observations. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *6118 LNAI* (PART 1), 391-402. https://doi.org/10.1007/978-3-642-13657-3_43

Barratt, T., Goods, C., & Veen, A. (2020). 'I'm my own boss…': Active intermediation and 'entrepreneurial' worker agency in the Australian gig-economy. *Environment and Planning A: Economy and Space*, *52*(8), 1643-1661. https://doi.org/10.1177/0308518X20914346

Belk, R. (2014). You are what you can access: Sharing and collaborative consumption online. *Journal of Business Research*, *67*(8), 1595-1600. https://doi.org/10.1016/j.jbusres.2013.10.001

Benoit, K., Watanabe, K., Wang, H., Nulty, P., Obeng, A., Müller, S., & Matsuo, A. (2018). quanteda: An R package for the quantitative analysis of textual data. *Journal of Open Source Software*, *3*(30), 774. https://doi.org/10.21105/joss.00774

Biraglia, A., & Kadile, V. (2017). The role of entrepreneurial passion and creativity in developing entrepreneurial intentions: Insights from American homebrewers. *Journal of Small Business Management*, *55*(1), 170-188. https://doi.org/10.1111/jsbm.12242

Blei, D. M., Ng, A. Y., & Edu, J. B. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research*, *3*(4-5), 993-1022. http://doi/10.1162/jmlr.2003.3.4-5.993

Bolton, D. L., & Lane, M. D. (2012). Individual entrepreneurial orientation: Development of a measurement instrument. *Education and Training*, *54*(2/3), 219-233. https://doi.org/10.1108/00400911211210314

Broda, Kris. (2021). *Gig Economy – The Economic Backbone of the Future?* https://brodmin.com/case-studies/gig-economy-case-study/

Burke, A., & Cowling, M. (2019). The relationship between freelance workforce intensity, business performance and job creation. *Small Business Economics*, *55*, 399-413. https://doi.org/10.1007/s11187-019-00241-x

Burke, A., & Cowling, M. (2020). The role of freelancers in entrepreneurship and small business. *Small Business Economics*, *55*(2), 389-392. https://doi.org/10.1007/s11187-019-00239-5

Burtch, G., Carnahan, S., & Greenwood, B. N. (2018). Can you gig it? An empirical examination of the gig economy and entrepreneurial activity. *Management Science*, *64*(12), 5497-5520. https://doi.org/10.1287/mnsc.2017.2916

Cao, J., Xia, T., Li, J., Zhang, Y., & Tang, S. (2009). A density-based method for adaptive LDA model selection. *Neurocomputing*, 72(7-9), 1775-1781. https://doi.org/10.1016/j.neucom.2008.06.011

Cardon, M. S., Glauser, M., & Murnieks, C. Y. (2017). Passion for what? Expanding the domains of entrepreneurial passion. *Journal of Business Venturing Insights*, *8*, 24-32. https://doi.org/10.1016/j.jbvi.2017.05.004

Cardon, M. S., & Kirk, C. P. (2015). Entrepreneurial Passion as Mediator of the Self-Efficacy to Persistence Relationship. *Entrepreneurship: Theory and Practice*, *39*(5), 1027-1050. https://doi.org/10.1111/etap.12089

Cardon, M. S., Wincent, J., Singh, J., & Drnovsek, M. (2009). The nature and experience of entrepreneurial passion. *Academy of Management Review*, *34*(3), 511-532. https://doi.org/10.5465/AMR.2009.40633190

Carsrud, A. L., & Brännback, M. (2009). *Understanding the Entrepreneurial Mind*. Springer. https://doi.org/10.1007/978-1-4419-0443-0

Chalmers, D., & Matthews, R. (2019). Good to be bad: Should we be worried by the sharing economy? *Strategic Change*, *28*(6), 403-408. https://doi.org/10.1002/jsc.2295

Chan, K. R., Lou, X., Karaletsos, T., Crosbie, C., Gardos, S., Artz, D., & Ratsch, G. (2013). An empirical analysis of topic modeling for mining cancer clinical notes. *Proceedings - IEEE 13th International Conference on Data Mining Workshops, ICDMW 2013*, 56-63. https://doi.org/10.1109/ICDMW.2013.91

Cho, W., & Cho, S. E. (2020). Entrepreneurial challenges in business model for the gig economy: Agendas for research and business development. *International Journal of Entrepreneurship*, *24*(1), 1-11.

Choi, Y. H., & Choi, S. H. (2019). Comparative study of crossing the chasm in applying smart factory system for SMEs. *International Journal of Innovative Technology and Exploring Engineering*, *8*(8), 1017-1024.

Clarysse, B., Van Boxstael, A., & Van Hove, J. (2015). Linking founder identity, goals and performance: The role of professional and development passion. *75th Annual Meeting of the Academy of Management, AOM 2015*, 738-743. https://doi.org/10.5465/AMBPP.2015.261

Codagnone, C., Biagi, F., & Abadie, F. (2016). The Passions and the Interests: Unpacking the "Sharing Economy." Science for Policy Report. European Union. https://doi.org/10.2139/ssrn.2793901

Daniel, F., Weston, S., & Tenenbaum, D. (2022). doParallel: Fore-ach parallel adaptor for the 'parallel' package. R package version 1.0.15. url: https://github.com/RevolutionAnalytics/doparallel.

Dempsey, D., & Jennings, J. (2014). Gender and entrepreneurial self-efficacy: A learning perspective. *International Journal of Gender and Entrepreneurship*, *6*(1), 28-49. https://doi.org/10.1108/IJGE-02-2013-0013

Deveaud, R., San Juan, E., & Bellot, P. (2014). Accurate and effective Latent Concept Modeling for ad hoc information retrieval. *Document Numerique*, *17*(1), 61-84. https://doi.org/10.3166/dn.17.1.61-84

Feinerer, I. (2015). Introduction to the tm Package: Text Mining in R. *R Vignette*, 1-8.

Ferrara, E., De Meo, P., Fiumara, G., & Baumgartner, R. (2014). Web data extraction, applications and techniques: A survey. *Knowledge-Based Systems*, *70*, 301-323. https://doi.org/10.1016/j.knosys.2014.07.007

Gandini, A. (2016). Digital work: Self-branding and social capital in the freelance knowledge economy. *Marketing Theory*, *16*(1), 123-141. https://doi.org/10.1177/1470593115607942

Geissinger, A., Laurell, C., Sandström, C., Eriksson, K., & Nykvist, R. (2019). Digital entrepreneurship and field conditions for institutional change– Investigating the enabling role of cities. *Technological Forecasting and Social Change*, *146*, 877-886. https://doi.org/10.1016/j.techfore.2018.06.019

Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(SUPPL. 1), 5228-5235. https://doi.org/10.1073/pnas.0307752101

Grün, B., Blei, D. M., Lafferty, J. D., Phan, X.-H., Matsumoto, M., & Nishimura, T. (2021). *Package 'topicmodels'*.

Hallak, R., Lindsay, N. J., & Brown, G. (2011). Examining the role of entrepreneurial experience and entrepreneurial self-efficacy on SMTE performance. *Tourism Analysis*, *16*(5), 583-599. https://doi.org/10.3727/108354211X13202764960744

Hannigan, T. R., Haans, R. F. J., Vakili, K., Tchalian, H., Glaser, V. L., Wang, M. S., Kaplan, S., & Jennings, P. D. (2019). Topic modeling in management research: Rendering new theory from textual data. *Academy of Management Annals*, *13*(2), 586-632. https://doi.org/10.5465/annals.2017.0099

Hornik, K., & Grün, B. (2011). Topicmodels: An R package for fitting topic models. *Journal of Statistical Software*, *40*(13), 1-30.

Huarng, K. H. (2018). Entrepreneurship for long-term care in sharing economy. *International Entrepreneurship and Management Journal*, *14*(1), 97-104. https://doi.org/10.1007/s11365-017-0460-9

Inoue, M., Fukahori, H., Matsubara, M., Yoshinaga, N., & Tohira, H. (2023). Latent Dirichlet allocation topic modeling of free-text responses exploring the negative impact of the early COVID-19 pandemic on research in nursing. *Japan Journal of Nursing Science*, *20*(2), e12520. https://doi.org/10.1111/jjns.12520

Jolliffe, I. T. (2002). *Principal Component Analysis* (2nd ed.). Springer-Verlag. https://doi.org/10.1007/b98835

Jollife, I. T., & Cadima, J. (2016). Principal component analysis: A review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences,* 374, 20150202. https://doi.org/10.1098/rsta.2015.0202

Katz, L. F., & Krueger, A. B. (2019). The rise and nature of alternative work arrangements in the United States, 1995-2015. *ILR Review*, 72(2), 382-416. https://doi.org/10.1177/0019793918820008

Klarin, A., & Suseno, Y. (2021). A state-of-the-art review of the sharing economy: Scientometric mapping of the scholarship. *Journal of Business Research*, *126*, 250-262. https://doi.org/10.1016/j.jbusres.2020.12.063

Kost, D., Fieseler, C., & Wong, S. I. (2020). Boundaryless careers in the gig economy: An oxymoron? *Human Resource Management Journal*, *30*(1), 100-113. https://doi.org/10.1111/1748-8583.12265

Koyuncu, İ., & Kılıç, A. F. (2019). The use of exploratory and confirmatory factor analyses: A document analysis. *Egitim ve Bilim*, 44(198), 361–388. https://doi.org/10.15390/EB.2019.7665

Lakshminarayanan, B., & Raich, R. (2011). Inference in supervised latent Dirichlet allocation. *IEEE International Workshop on Machine Learning for Signal Processing, pp. 1-6.* https://doi.org/10.1109/MLSP.2011.6064562

Larsson, A., & Teigland, R. (2020). *The Digital Transformation of Labor: Automation, the Gig Economy and Welfare*. Routledge.

Li, C., Murad, M., Shahzad, F., Khan, M. A. S., Ashraf, S. F., & Dogbe, C. S. K. (2020). Entrepreneurial passion to entrepreneurial behavior: Role of entrepreneurial alertness, entrepreneurial self-efficacy and proactive personality. *Frontiers in Psychology*, *11*, 1611. https://doi.org/10.3389/fpsyg.2020.01611

Liang, X., Jiang, J., & Li, E. Y. (2018). IT-based entrepreneurship in sharing economy: The mediating role of value expectancy in micro-entrepreneur's passion and persistence. *International Journal of Information Systems and Change Management*, *10*(4), 352-373. https://doi.org/10.1504/IJISCM.2018.098400

Liao, Y. K., Nguyen, V. H. A., & Caputo, A. (2022). Unveiling the role of entrepreneurial knowledge and cognition as antecedents of entrepreneurial intention: A meta-analytic study. *International Entrepreneurship and Management Journal*, *18*, 1623-1652. https://doi.org/10.1007/s11365-022-00803-8

Liguori, E. W., Bendickson, J. S., & McDowell, W. C. (2018). Revisiting entrepreneurial intentions: a social cognitive career theory approach. *International Entrepreneurship and Management Journal*, *14*(1), 67-78. https://doi.org/10.1007/s11365-017-0462-7

Liñán, F., & Santos, F. J. (2007). Does social capital affect entrepreneurial intentions? *International Advances in Economic Research*, *13*(4), 443-453. https://doi.org/10.1007/s11294-007-9109-8

Lucas, A. C., & Tingley, D. (2015). *Package 'translateR.'* 1-7.

Lumpkin, G. T., Steier, L., & Wright, M. (2011). Strategic Entrepreneurship in Family Business. *Strategic Entrepreneurship Journal*, *5*(4), 285-306. https://doi.org/10.1002/sej.122

Maier, D., Waldherr, A., Miltner, P., Wiedemann, G., Niekler, A., Keinert, A., Pfetsch, B., Heyer, G., Reber, U., Häussler, T., Schmid-Petri, H., & Adam, S. (2018). Applying LDA topic modeling in communication research: Toward a valid and reliable methodology. *Communication Methods and Measures*, *12*(2-3), 93-118. https://doi.org/10.1080/19312458.2018.1430754

Md Isa, F., Jaganathan, M., Sern, V. Y. C., Ahmdon, M. A. S., & Nafi, S. N. M. (2020). Does service marketing enhance supplier and customer contact in the gig economy era? Case analysis from Malaysian SMEs women entrepreneurs. *International Journal of Supply Chain Management*, *9*(1), 1105-1113.

Memon, M., Soomro, B. A., & Shah, N. (2019). Enablers of entrepreneurial self-efficacy in a developing country. *Education and Training*, *61*(6), 684–699. https://doi.org/10.1108/ET-10-2018-0226

Mimno, D., Wallach, H., & Mccallum, A. (2008). Gibbs sampling for logistic normal topic models with graph-based priors. *Nips*, 1-8. http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Gibbs+Sampling+for+Logistic+Normal+Topic+Models+with+-Graph-Based+Priors#0

Murnieks, C. Y., Cardon, M. S., & Haynie, J. M. (2020). Fueling the fire: Examining identity centrality, affective interpersonal commitment and gender as drivers of entrepreneurial passion. *Journal of Business Venturing*, *35*(1), 105909. https://doi.org/10.1016/j.jbusvent.2018.10.007

Netto, C. de O., & Tello-Gamarra, J. E. (2020). Sharing economy: A bibliometric analysis, research trends and research agenda. *Journal of Technology Management and Innovation*, *15*(2), 41-55. https://doi.org/10.4067/s0718-27242020000200041

Newman, D., Asuncion, A., Smyth, P., & Welling, M. (2009). Distributed algorithms for topic models published 8/09. *Journal of Machine Learning Research*, *10*, 1801-1828.

Norena-Chavez, D., & Guevara, R. (2020). Entrepreneurial Passion and Self-Efficacy as Factors Explaining Innovative Behavior: A Mediation Model. *International Journal of Economics and Business Administration*, *8*(3), 352-373. https://doi.org/10.35808/ijeba/522

Ogunleye, B., Maswera, T., Hirsch, L., Gaudoin, J., & Brunsdon, T. (2023). Comparison of Topic Modelling Approaches in the Banking Context. *Applied Sciences (Switzerland)*, *13*(2), 797. https://doi.org/10.3390/app13020797

Ooms, J. (2022). *Package 'pdftools'* (3.30). CRAN.

Pankov, S., Velamuri, V. K., & Schneckenberg, D. (2021). Towards sustainable entrepreneurial ecosystems: Examining the effect of contextual factors on sustainable entrepreneurial activities in the sharing economy. *Small Business Economics*, *56*(3), 1073-1095. https://doi.org/10.1007/s11187-019-00255-5

Pfitzner-Eden, F. (2016). Why do I feel more confident? Bandura's sources predict preservice teachers' latent changes in teacher self-efficacy. *Frontiers in Psychology*, *7*, 1486. https://doi.org/10.3389/fpsyg.2016.01486

Poon, T. S. C. (2019). Independent workers: Growth trends, categories, and employee relations implications in the emerging gig economy. *Employee Responsibilities and Rights Journal*, *31*(1), 63-69. https://doi.org/10.1007/s10672-018-9318-8

R Core Team (2022). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/

Ravenelle, A. J. (2019). "We're not uber:" control, autonomy, and entrepreneurship in the gig economy. *Journal of Managerial Psychology*, *34*(4), 269-285. https://doi.org/10.1108/JMP-06-2018-0256

Ray, T. K., & Pana-Cryan, R. (2021). Work flexibility and work-related well-being. *International Journal of Environmental Research and Public Health*, *18*(6), 1-17. https://doi.org/10.3390/ijerph18063254

Roxas, B. (2014). Effects of entrepreneurial knowledge on entrepreneurial intentions: A longitudinal study of selected South-east Asian business students. *Journal of Education and Work*, *27*(4), 432-453. https://doi.org/10.1080/13639080.2012.760191

Sagadevan, S., Malim, N. H. A. H., & Husin, M. H. (2022). A Seed-guided Latent Dirichlet allocation approach to predict the personality of online users using the PEN model. *Algorithms*, *15*(3), 87. https://doi.org/10.3390/a15030087

Santamaría, L., & Mihaljević, H. (2018). Comparison and benchmark of name-to-gender inference services. *PeerJ Computer Science*, 4, e156. https://doi.org/10.7717/peerj-cs.156

Santos, G., Marques, C. S., & Ferreira, J. J. M. (2020). Passion and perseverance as two new dimensions of an Individual Entrepreneurial Orientation scale. *Journal of Business Research*, *112*, 190-199. https://doi.org/10.1016/j.jbusres.2020.03.016

Scheepers, C. B., & Bogie, J. (2020). Uber Sub-Saharan Africa: contextual leadership for sustainable business model innovation during COVID-19. *Emerald Emerging Markets Case Studies*, *10*(3), 1-18. https://doi.org/10.1108/EEMCS-05-2020-0165

Schmidt, F. A. (2017). *Digital Labour Markets in the Platform Economy Mapping the Political Challenges of Crowd Work and Gig Work*. Friedrich-Ebert-Stiftung. http://library.fes.de/pdf-files/wiso/13164.pdf

Shahrakipour, H. (2021). Psychometric Characteristics of a Questionnaire Measuring Hopefulness: An Exploratory and Confirmatory Factor Analysis Approach. *Health Scope*, 10(4). https://doi.org/10.5812/jhealthscope.119157

Silva, B. C., & Moreira, A. C. (2022). Entrepreneurship and the gig economy: A bibliometric analysis. *Cuadernos de Gestion*, *22*(2), 23-44. https://doi.org/10.5295/cdg.211580am

Sobakinova, D., Zhou, Y., & Durrani, D. K. (2020). The role of human capital outcomes in generating business ideas. *VINE Journal of Information and Knowledge Management Systems*, *50*(1), 163-183. https://doi.org/10.1108/VJIKMS-03-2019-0033

Sosianika, A., Suhaeni, T., Wibisono, N., & Suhartanto, D. (2018). *The Dimension of Food Souvenir: An Exploratory-Confirmatory Factor Analysis*. MATEC Web of Conferences, 218. https://doi.org/10.1051/matecconf/201821804002

Sulistyani, N. W., Suhariadi, F., & Fajrianthi. (2022). Self-efficacy as a mediator of the impact of social capital on entrepreneurial orientation: A case of Dayak Ethnic Entrepreneurship. *Sustainability (Switzerland)*, *14*(9), 5620. https://doi.org/10.3390/su14095620

Team, R. C. (2018). *R: A language and environment for statistical computing. R Foundation for Statistical Computing*.

Trabucchi, D., Muzellec, L., & Ronteau, S. (2019). Sharing economy: Seeing through the fog. *Internet Research*, *29*(5), 996-1013. https://doi.org/10.1108/INTR-03-2018-0113

Turner, B. (2023). Digital working lives: Worker autonomy and the gig-economy. *Contemporary Political Theory*. https://doi.org/10.1057/s41296-023-00619-3

UNCTAD. (2018). 2018 Annual Report Highlights. *United Nations*.

United Nations. (2020). *Entrepreneurship for sustainable development: Report of the Secretary-General*. *10151*(July), 19.

Vallerand, R. J., Mageau, G. A., Ratelle, C., Léonard, M., Blanchard, C., Koestner, R., Gagné, M., & Marsolais, J. (2003). Les passions de l'âme: On obsessive and harmonious passion. *Journal of Personality and Social Psychology*, *85*(4), 756-767. https://doi.org/10.1037/0022-3514.85.4.756

Vamvaka, V., Stoforos, C., Palaskas, T., & Botsaris, C. (2020). Attitude toward entrepreneurship, perceived behavioral control, and entrepreneurial intention: dimensionality, structural relationships, and gender differences. *Journal of Innovation and Entrepreneurship*, *9*, 5. https://doi.org/10.1186/s13731-020-0112-0

Vasques, R. A., Koria, M., & Santos, M. C. L. dos. (2017). Why do I love you Vaatelainaamo? Analysis of motivations, barriers and opportunities in a Finnish service for sharing clothes. *Design Journal*, *20*(sup1), S721-S731. https://doi.org/10.1080/14606925.2017.1353018

Wach, K., Glodowska, A., & Maciejewski, M. (2018). Entrepreneurial orientation, knowledge utilization and internationalization of firms. *Sustainability (Switzerland)*, *10*(12), 4711. https://doi.org/10.3390/su10124711

Wais, K. (2016). Gender prediction methods based on first names with genderizeR. *R Journal*, *8*(1), 17-37. https://doi.org/10.32614/rj-2016-002

Wallach, H. M., Murray, I., Salakhutdinov, R., & Mimno, D. (2009). Evaluation methods for topic models. *Proceedings of the 26th International Conference on Machine Learning*, Montreal, Canada.

Wang, C., Mundorf, N., & Salzarulo-Mcguigan, A. (2021). Psychological well-being sustainable during entrepreneurial process-the moderating role of entrepreneurial creativity. *Sustainability (Switzerland)*, *13*(19), 732. https://doi.org/10.3390/su131910732

Williamson, A. J., Battisti, M., & Pollack, J. M. (2022). Capturing passion expressed in text with artificial intelligence (AI): Affective passion waned, and identity centrality was sustained in social ventures. *Journal of Business Venturing Insights*, *17*, e00295. https://doi.org/10.1016/j.jbvi.2021.e00295

Yitshaki, R., & Kropp, F. (2016). Entrepreneurial passions and identities in different contexts: a comparison between high-tech and social entrepreneurs. *Entrepreneurship and Regional Development*, *28*(3-4), 206–233. https://doi.org/10.1080/08985626.2016.1155743

Yuan, F., Woodman, R. W., Yuan, F., & Woodman, R. W. (2016). Innovative behavior in the workplace: The role of performance and image outcome expectations. *The Academy of Management Journal*, *53*(2), 323-342.

Zhang, T., Bufquin, D., & Lu, C. (2019). A qualitative investigation of microentrepreneurship in the sharing economy. *International Journal of Hospitality Management*, *79*, 148-157. https://doi.org/10.1016/j.ijhm.2019.01.010

Zhao, H., Hills, G. E., & Seibert, S. E. (2005). The mediating role of self-efficacy in the development of entrepreneurial intentions. *Journal of Applied Psychology*, *90*(6), 1265-1272. https://doi.org/10.1037/0021-9010.90.6.1265

Zhu, H., Travison, T., Tsai, T., Beasley, W., Xie, Y., Yu, G., Laurent, S., Shepherd, R., Sidi, Y., Salzer, B., Gui, G., Fan, Y., Murdoch, D., & Evans, B. (2021). KableExtra: construct complex table with "kable" and pipe syntax. https://rdrr.io/cran/kableExtra/.