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Driving Forces Shaping Gig Economy Perceptions in Mongolia: A Multifactorial PLS-SEM Approach

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Abstract

The gig economy, characterized by flexible, task-based, and technology-driven work, has become an increasingly important aspect of modern labor markets, especially in emerging economies. This study aims to assess the perceptions of the gig economy in Mongolia by examining the influence of five main factors: economic, social, technological, personal, and work-environmental. Using the Partial Least Squares Structural Equation Modelling (PLS-SEM) framework, data were collected through a structured questionnaire (Likert Scale) distributed to 43 participants in Mongolia. The results revealed mixed findings across the hypothesized relationships. Economic factors significantly influenced perceptions of the gig economy (H1: $\beta = 0.207$, $p = 0.014$), but their impact on the gig work environment was not supported (H1a: $\beta = 0.339$, $p = 0.069$). Social factors did not significantly influence gig economy perceptions (H2: $\beta = 0.254$, $p = 0.111$), but they had a positive impact on the gig work environment (H2a: $\beta = 0.431$, $p = 0.023$). Technological factors positively influenced gig economy perceptions (H3: $\beta = 0.035$, $p = 0.042$). However, personal factors did not have a significant impact (H4: $\beta = 0.251$, $p = 0.116$). Finally, the gig work environment positively influenced perceptions of the gig economy (H5: $\beta = 0.247$, $p = 0.008$). These findings highlight the multifaceted and complex nature of gig economy perceptions in Mongolia, highlighting the importance of economic and technological factors as well as the role of the work environment in shaping overall perceptions. This study contributes to a deeper understanding of the driving forces behind gig economy perceptions in emerging economies such as Mongolia.

Keywords:
Gig Economy;
PLS-SEM;
Mongolia;
Freelance Work;
Flexible Employment.

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1- Introduction

In today's labor market, freedom often refers to the capacity to customize work to meet personal goals and desires without being constrained by the tight frameworks imposed by traditional employment. This concept has become increasingly relevant in the AI-driven era, where the search for financial, social, and economic freedom is reshaping the global workforce. The gig economy embodies this freedom, offering people the flexibility and control to define their own work schedules and opportunities [1, 2]. By leveraging technology, people are increasingly breaking away from traditional jobs to achieve the liberty they desire in both their personal and professional lives [3-5].

The gig economy has emerged as a transformative and driven force in the global labor market, fundamentally changing traditional employment patterns and redefining how work is performed and paid [3, 6, 7]. Powered by short-term, flexible, and task-based relationships supported by digital platforms, the gig economy has grown significantly over the past decade as a result of rapid technological advancements, shifts in customer preferences, and changing economic conditions. The term "gig economy" became prominent at the end of the 1990s and early 2000s, reflecting the increasing

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reliance on temporary and freelance work concepts [8]. It has since become a central focus of academic, policy, and industry discussions, given its implications for labor and the whole economy.

Because of the multifaceted nature of the gig economy concept, several definitions of it have appeared from various organizations, governments, and individuals (e.g., researchers, economists, and industry experts). Each definition highlights different aspects of the gig economy, from the technological foundations to social and economic implications. For example, the International Labor Organization (ILO) defines the gig economy as "a labor market that is characterized by independent contracting that happens through, via, and on digital platforms" [9]. Similarly, the U.S. Bureau of Labor Statistics, a unit of the United States Department of Labor, defines the gig economy as "a gig describes a single project or task for which a worker is hired, often through a digital marketplace, to work on demand" [10]. In addition to these institutional definitions, many scholars have presented their own definitions of the gig economy, often focusing on the main aspects of it, such as flexibility, task-based employment, or the role of technology in mediating work [7, 11, 12]. Based on these different definitions, this study uses the "gig economy" term to refer to dynamic jobs that are characterized by flexible, freelance, and task-based jobs, supported by advanced technology and digital platforms.

In developing countries such as Mongolia, the gig economy presents unique opportunities and challenges [13, 14]. It has the potential to reduce unemployment, encourage entrepreneurship, and link locals in rural areas to urban/city markets. However, limited access to digital infrastructure and financial systems presents major barriers to participation. Additionally, the absence of clear regulations and protections for gig workers reduces their adoption. Understanding how the gig economy works in such contexts is very important to developing inclusive and sustainable policies that maximize its benefits while addressing its limitations.

The gig economy in Mongolia is becoming an increasingly important component of the country's economic landscape, especially when linked with the inflation percentages. In Figure 1, Mongolia's GDP has experienced fluctuations over the years, with notable peaks and drops, while inflation rates have shown considerable volatility [15, 16]. By giving workers new sources of income and encouraging entrepreneurship, the gig economy (which is defined by flexible and technologically advanced job opportunities) can stabilize key economic indicators (e.g., GDP and inflation rate). Also, by offering substitute job possibilities, the gig economy can serve as a buffer during times of slow GDP growth, as well as reduce the effects of recessions. On the other hand, the gig economy's accessibility and low entry challenges might help people improve their incomes during periods of high inflation, allowing them to adapt to rising expenses.

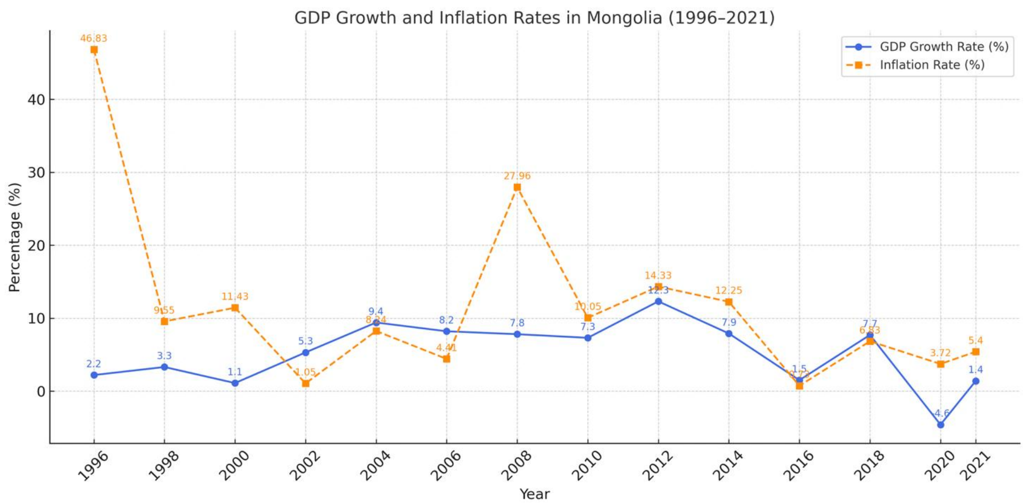

Figure 1. **GDP growth and Inflation rates in Mongolia**

Recent studies have increasingly focused on how individuals perceive and experience work in the gig economy, with an emphasis on psychological, technological, structural, and contextual aspects. For example, Wan et al. (2024), in their study, examine the paradox of autonomy in platform work, demonstrating that although autonomy is a key attraction of gig work, it is frequently compromised by algorithmic control. Their research indicates that cognitive and emotional processes, specifically work alienation and positive emotion, mediate the link between job autonomy and workplace well-being. This dual-path model provides a more precise understanding of how workers perceive autonomy within technologically controlled environments, stressing the importance of considering system-level constraints alongside individual-level motivations [17]. Expanding on this topic, Kurian and Madhavi (2024) analyze the motivations and well-being of Gen Y and Gen Z gig workers in low-skilled, app-based services. Utilizing self-determination theory and the Job Demands-Resources (JDR) model, they identify autonomy, flexibility, and financial independence as primary motivators, while also recognizing stress, job insecurity, and the absence of formal protections as significant challenges. Their findings underscore the importance of intrinsic and extrinsic motivators in influencing gig workers' quality of life, while highlighting the moderating role of individual attributes such as resilience and digital skills [18].

From a systems safety perspective, Salmon et al. (2023) conduct a thorough multi-level analysis of the behaviors exhibited by gig delivery riders. Their research uncovers that safety outcomes are influenced by a broad network of stakeholders, including platforms, infrastructure providers, customers, and regulators, rather than solely by the workers themselves. The study highlights the necessity of systemic interventions, rather than focusing on individuals, to enhance safety and performance in platform-based delivery work, particularly under conditions of time pressure and financial insecurity [19]. On the user side of the gig economy, Tripathi et al. (2022) investigate client perceptions of physical gig services. Their model pinpoints hedonic motivation, economic benefit, and trust as the most significant factors driving behavioral intention, while social influence and perceived risk are less influential. This study emphasizes the importance of platform design, responsiveness, and data security in shaping consumer engagement and advocates for multi-stakeholder approaches in comprehending gig service ecosystems [20]. In another study, Himani et al. (2025) offer a worldwide overview through a bibliometric analysis of gig economy literature, pinpointing eight main research clusters that pertain to worker well-being, digital platforms, and employment conditions. They draw attention to increasing worries about algorithmic control, labor insecurity, and the decline of traditional employment protections, especially in lower- and middle-income nations. The authors stress the importance of conducting regional and sector-specific research that considers structural inequalities and the fast-changing landscape of digital work [21].

Although the previously reviewed studies offer valuable insights into aspects such as worker motivation, platform design, user behavior, and global research trends within the gig economy, they also uncover significant research gaps. Firstly, most existing research focuses on digitally advanced or highly urbanized areas, with minimal empirical exploration of transitional or underrepresented contexts like Mongolia. Secondly, while many influencing factors such as motivation, safety, autonomy, and client perception have been examined independently, there is a shortage of studies employing a multifactorial analytical approach to understand the combined effects of social, economic, personal, and technological dimensions. Thirdly, the use of advanced statistical models, such as PLS-SEM, is notably limited in analyzing public perceptions of the gig economy, especially in developing regions such as Mongolia.

Accordingly, this study focuses on presenting the perceptions of the gig economy from the perspective of the Mongolian people. By examining their views through different dimensions (e.g., economic, social, personal, technological, and work-environmental), this study aims to provide a comprehensive understanding of how the gig economy is perceived and its role in the Mongolian labor market. From an economic perspective, the findings of this study help in developing strategies to enhance the gig economy as a tool for reducing unemployment and providing alternative income opportunities, especially during uncertain or slow GDP development periods. From the social perspective, this study can help in clarifying how Mongolian community acceptance and support networks influence individuals' decisions to participate in gig work, offering insights into fostering inclusivity and reducing social stigma around non-traditional employment like gig work. From personal factors, understanding how flexibility, skills alignment, and lifestyle compatibility shape perceptions can help gig platforms be designed to better serve workers' requirements. Also, this study's focus on technology highlights the importance of digital infrastructure and platform usability in enhancing gig work, which can encourage investment in technological advancements and digital literacy programs. Finally, examining the gig economy as a work environment, including aspects like job stability and growth opportunities, can help address challenges related to worker rights, equitable pay, and long-term career development.

The remainder of this article is organized as follows. Section 2 presents a review of the relevant literature and the development of research hypotheses. Section 3 describes the research methodology, including data collection procedures and the PLS-SEM modelling approach. Section 4 reports the results of the data analysis. Section 5 discusses the findings in relation to previous studies and the specific context of Mongolia. Finally, Section 6 concludes the study, highlights its limitations, and suggests directions for future research.

2- Literature Review and Hypotheses Development

Although the gig economy workforce remains small compared to traditional employment sectors [7], it is expanding rapidly due to several key factors, including economic conditions, social factors, technological advances, personal preferences, and work-environment factors. This led to a wide range of perceptions about the gig economy, which are explored in various scholarly literature. For example, the economic factors (e.g., reduced unemployment rates, increased income opportunities, increased entrepreneurial opportunities, and enhanced market efficiency) are fundamental in shaping positive perceptions of the gig economy. For example, gig work provides a reliable source of additional income for individuals, especially for people who are unable to commit to a regular full-time job or who want to increase their income for different reasons [22-24].

Additionally, gig work often offers fair pay for the required efforts and the invested time. Services such as Uber, for example, enable drivers to get paid according to the number of rides or deliveries they make, sometimes with the possibility of earning more through tips or surge pricing during peak periods [25, 26]. Furthermore, gig work helps improve workers' financial situation by providing accessible and flexible earning options. It enables people to increase economic stability, lessen financial burdens, and produce more revenue. Gig platforms, for example, allow workers to adapt to their financial needs by taking on more work during times of economic hardship or the rise of unexpected bills [27, 28]. This flexibility improves workers' overall financial well-being by helping them avoid the absence of traditional employment, save for future desires, or bridge income gaps. Accordingly, the following hypotheses are proposed:

H1: *Economic factors positively influence the perception of the gig economy.*

H1a: *Economic factors positively influence the perception of the gig economy as a work environment.*

The perception of the gig economy is not only influenced by economic factors but also deeply rooted in social factors, which, in many cases, influence individuals' decisions to engage in this form of work. According to the Theory of Planned Behavior, behavioral intentions are greatly influenced by subjective norms, which are defined as the perceived social pressure to engage in or refrain from engaging in a behavior [29]. People are more inclined to see gig work favorably and think of it as a feasible career option when they feel encouraged and supported by friends, family, or coworkers [30, 31]. For example, research indicates that people who get encouraging feedback from their social networks are more likely to be satisfied and confident when engaging in the gig economy [32, 33].

Additionally, gig employment perceptions are greatly influenced by community acceptance [3]. Cultural standards, the state of the economy, and the growing importance of gig platforms in a particular area/region all have an impact on the gig economy perceptions. In these communities, people are more likely to view gig work as a respectable and legal type of job [4, 34]. This normalization encourages wider engagement and participation in gig jobs. Furthermore, external encouragement is another important social factor. Friends' and family recommendations, success stories, and verbal encouragement may all have a favorable impact on an individual's decision to join the gig economy [30, 31]. This kind of support creates a sense of societal acceptance and lowers the perceived dangers connected to unusual work arrangements. According to empirical research, people who get encouragement from their social networks are more motivated to join gig work and have positive perceptions of it [35, 36]. Based on this, the following two hypotheses are proposed:

H2: *Social factors positively influence the perception of the gig economy.*

H2a: *Social factors positively influence the perception of the gig economy as a work environment.*

Technological factors play a key role in fostering positive perceptions of the gig economy, since it as a whole is mostly dependent on digital platforms and technology infrastructure. The accessibility and usability of gig platforms are important factors [37]. Gig workers benefit from user-friendly interfaces and simple navigation methods that make it easier for them to locate and complete tasks quickly and without any technological difficulties. Because of this seamless technology and the motivations for participation in gig work, many studies have demonstrated that platform design simplicity and dependability influence user satisfaction and desire to engage in gig work [6, 21, 38, 39]. Also, the availability of necessary technologies, such as smartphones, computers, and internet connectivity, plays a vital role in motivating workers to participate in the gig economy. This was highlighted in many studies where access to technology is a key determinant of who can join gig platforms, as those with the required tools are more likely to take advantage of these opportunities [40-42]. Moreover, technology makes gig work more convenient, which further contributes to favorable perceptions. For gig workers, digital platforms provide advantages like real-time updates, flexible scheduling, and rapid communication that make the process easier. For example, gig platforms, such as Uber and DoorDash, provide users with real-time notifications, location tracking, and automated payment systems, all of which contribute to a sense of efficiency and control [26, 36]. This technological convenience allows gig workers to manage their work schedules more effectively, as well as align their work with their personal lives and preferences. Consequently, the following hypothesis is proposed:

H3: *Technological factors positively influence the perception of the gig economy.*

Moving to the personal factors group, which has been highlighted in many gig economy studies for its important role in shaping perceptions of this type of work [43]. One of these personal preferences is the alignment of the gig economy with the personal needs and lifestyles of many people (e.g., millennials, students, women, and retirees). The unique flexibility that gig work offers allows people to select tasks and work that suit their skills [44, 45]. Another important personal factor is the suitability of gig work for individual schedules. Gig work gives individuals the flexibility to choose when and how long they work, in contrast to typical employment types that have a restricted set of hours [1, 2]. People who want to control their schedule, such as those who need to adjust to changing obligations or want to work during off-peak hours, can particularly benefit from this flexibility. According to studies, this flexibility of gig work not only improves work-life balance but also raises satisfaction and strengthens the gig economy's positive reputation [2, 3, 5, 23]. Additionally, the possibility to leverage personal skills in the gig work enhances its appeal. Gig platforms cater to a wide range of skills, from creative talents (e.g., graphic design and writing) to service roles (e.g., delivery and ride-sharing). This diversity allows people to make money off of their unique skills, boosting their confidence and sense of independence [3]. Various studies suggested that workers who believe their skills are suitable for gig opportunities are more likely to have a positive perception of the gig economy, as it gives them a chance to show their abilities and gain financial rewards [46-48]. As a result, the following hypnosis was developed:

H4: *Personal factors positively influence the perception of the gig economy.*

The fourth and final factor group is work-environment factors, which play a significant role in shaping overall perceptions of the gig economy. Opportunities for long-term growth are an important aspect of this relationship. Many gig platforms offer tools for professional development and skill enhancement, such as rating systems, specialized training, or access to premium tasks for high-performing workers [31, 36]. Workers often have a more positive perception of gig work when they see opportunities for professional growth. This is particularly evident in fields like freelancing, where professionals can build their portfolios, attract higher-paying clients, establish themselves as experts, and highlight the positive aspects of gig work [4, 35, 49, 50]. For example, Upwork, a freelancing platform, offers features that build a possible strong relationship between freelancers and clients. The platform encourages freelancers to get recurring contracts by highlighting repeat clients as a sign of success [51]. Working with a select group of regular clients has allowed many Upwork freelancers to establish full-time jobs and guarantee a continuous flow of revenue. Similarly, Fiverr, another freelance platform, offers subscription-based services, allowing clients to engage their services on a monthly or recurring basis [51]. This feature allows gig workers to secure stable, predictable income streams over time and eventually contributes to their perception of gig work as a reliable work type. Additionally, the ability of gig work to provide financial stability and security contributes to its positive perception of a work environment. Many workers say that the flexibility of gig platforms enables them to strategically manage their money, even though gig employment is frequently linked to income fluctuation [4, 22, 44]. For example, the ability to take on additional tasks during periods of higher service demand or to save earnings from peak work periods supports workers' financial stability. Accordingly, gig workers are more likely to see the gig economy as a legitimate and long-term job type when they can plan and achieve financial stability. Consequently, the following hypothesis was formulated:

H5: *Work-environment factors positively influence the perception of the gig economy.*

Accordingly, this study aims to examine the previously mentioned hypotheses by using the Partial Least Squares Structural Equation Modelling (PLS-SEM) as the main analytical framework. By analyzing the collected data through a structured questionnaire, this study aims to provide empirical insights into how economic, social, technological, personal, and work-environmental factors shape overall perceptions of the gig economy. Figure 2 presents the conceptual model based on the formulated hypotheses.

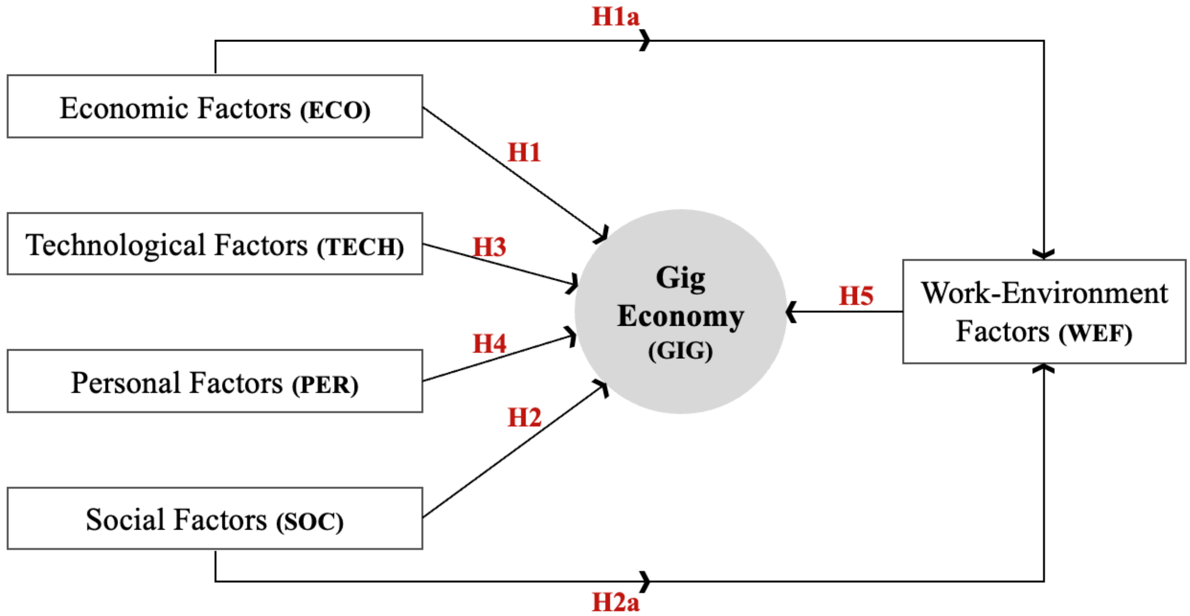

Figure 2. Conceptual and hypothetical model

3- Research Methodology

To better understand perceptions of the gig economy in Mongolia and evaluate the proposed hypotheses, this study employed Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS 4 software. PLS-SEM is a statistical framework that analyzes complex relationships between variables by assessing measurement and structural models [52]. The choice of PLS-SEM as the main method for this study was based on four key reasons. First, PLS-SEM is well-suited for analyzing complex relationships among multiple constructs and indicators, such as those in this study. Second, it aligns perfectly with the exploratory nature of this research, which seeks to identify preliminary relationships shaping perceptions of the gig economy in Mongolia. Given the small sample size, PLS-SEM is particularly effective, as it performs well with small to moderate sample sizes, unlike traditional covariance-based SEM methods. Third, PLS-SEM emphasizes predictive relevance (Q^2) and explanatory power (R^2), enabling the assessment of how well-selected factors predict perceptions of the gig economy in Mongolia. Finally, PLS-SEM's ability to deliver reliable results without requiring strict data normality assumptions makes it an ideal choice for this study [52-54].

The PLS-SEM method used in this study is based on the five previously mentioned hypotheses. So, the model includes five. Exogenous constructs (economic factors, social factors, technological factors, personal factors, and work-environment factors) and one endogenous construct, the perception of the gig economy (see Figure 2). The model hypothesizes that each of the exogenous constructs positively influences the perception of the gig economy in Mongolia.

To collect the data, a structured questionnaire was designed using insights from existing literature and expert feedback. The questionnaire consisted of three main sections. The first section focused on the demographic data of the participants, including age, gender, education, and residential area. The second section included the main exogenous constructs and their items, measuring the Mongolian perspective on the gig economy. These items were measured using a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree), with three representative items for each exogenous construct (economic factors, social factors, technological factors, personal factors, and work-environment factors). The third and final section of the questionnaire addressed the perception of the gig economy as an endogenous construct, which was also represented by three items.

The study used a nonprobability/convenience sampling technique, which focuses on selecting participants based on their availability, accessibility, and willingness to participate rather than through random selection. The choice of this nonprobability technique was aligned with the main objectives of this research. Given the exploratory nature of the study, which aims to understand perceptions of the gig economy in Mongolia, convenience sampling allowed for efficient data collection from participants who were easily accessible and willing to engage. Consequently, 97 questionnaires were distributed online between December 2024 and January 2025 to participants across Mongolia. To ensure a representative sample, the survey was shared across different Mongolian regions to capture the population's diverse perceptions of the gig economy. Of these, 61 questionnaires were returned, yielding a response rate of approximately 60.91%. Due to missing data, 18 questionnaires were excluded while maintaining the convenience-based nature of the sample. The final sample consisted of 43 participants. While this number may appear small compared to typical SEM studies, several factors justify its adequacy. First, the gig economy in Mongolia is still emerging, with limited formalization and access to participants, especially beyond major urban areas like Ulaanbaatar. Second, rural areas face digital connectivity and literacy challenges, making online data collection particularly difficult. Third, many potential participants either did not self-identify as gig workers or were reluctant to share financial and employment details, a cultural hesitancy common in developing countries. Additionally, the choice of PLS-SEM, which is known for its robustness with small-to-moderate samples, further supports the appropriateness of the sample size. The sample also meets the “ten times rule” for model complexity, ensuring methodological soundness.

Table 1 and Figure 3 present the main demographic characteristics of the study's sample. The sample's demographic characteristics reveal a predominantly middle-aged, urban, and highly educated group. Most participants are aged 25 - 44 (88.3%), with minimal representation from younger (7%) and older respondents (4.7%). Females make up 65.1% of the sample, while males account for 34.9%. The sample is highly educated, with 95.3% holding a university degree, and is urban-centric, with 90.7% residing in cities and only 9.3% from rural areas. These characteristics reflect a population likely to have greater access to gig work platforms and may influence the perceptions explored in this study.

Table 1. Demographic characteristics

Category	Variables	Frequency	%
Age	Under 18	0	0
	18-24	3	7
	25-34	17	39.5
	35-44	21	48.8
	45-54	0	0
	55 and above	2	4.7
Gender	Male	15	34.9
	Female	28	65.1
Education Level	Less than high school	0	0
	High school diploma	2	4.7
	University education (bachelor's, master's, doctorate)	41	95.3
Residential Area	Urban (city)	39	90.7
	Rural (village)	4	9.3

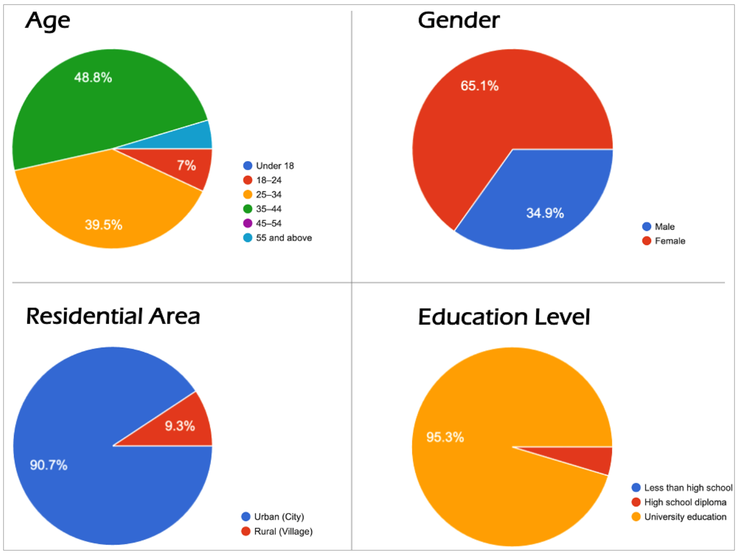

Figure 3. Demographic characteristics

4- Data Analysis and Results

4-1- Common Method Bias

Before delving into the results of the different PLS-SEM models, and to ensure the data validity, a Harman's single factor test was performed to check for potential common method bias. The results showed that the first factor explained 41.17% of the total variance, which is below the critical threshold of 50%. This result highlights that common method bias is not a significant concern for the validity of this study's outcomes.

4-2- PLS-SEM Models Analysis

The results of the PLS-SEM analysis are primarily illustrated in the following Figure 4, which presents the two key models: the structural model and the measurement model. This figure provides a comprehensive overview of the relationships between the constructs, highlighting the structural pathways and the reliability and validity of the measurement items. This PLS-SEM conceptual model addresses two main questions: how do different factors affect Mongolians' perception of the gig economy, and how do various economic and social factors influence their view of the gig economy as a working environment? The details of the structural model and the measurement model are presented as follows.

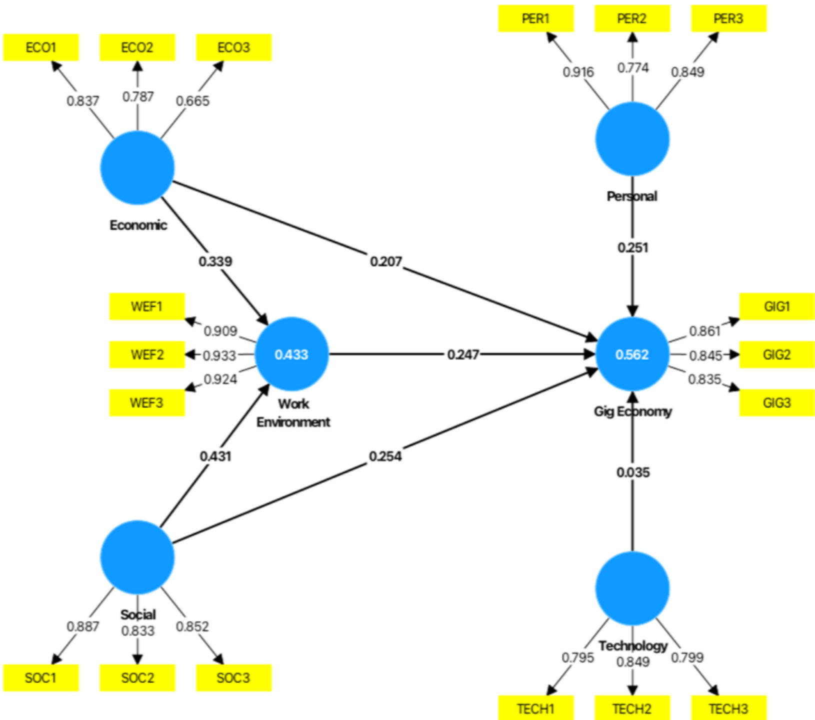

Figure 4. PLS-SEM model with path coefficient values and external loadings of latent reflective variables

4-2-1- Measurement Model Analysis

The measurement model in the PLS-SEM analysis focuses on ensuring that constructs such as Economic factors (ECO), Social factors (SOC), Technological factors (TECH), Personal factors (PER), Work Environment factors (WEF), and Gig Economy factors (GIG) are measured accurately using their respective items (e.g., ECO1, ECO2, etc.). This target is achieved by establishing the reliability and validity of the observed variables/items before proceeding to analyze the structural relationships between the exogenous constructs and the endogenous construct. This reliability and validity assessment is conducted through various techniques, including factor loadings, internal consistency reliability (e.g., Composite Reliability and Cronbach's Alpha), convergent validity (e.g., Average Variance Extracted - AVE), and discriminant validity (e.g., cross-loading, Fornell-Larcker Criterion, and Heterotrait-Monotrait Method - HTMT), which are presented as follows.

The following Table 2 presents the results of factor/outer loadings, which can also be seen in Figure 2. These factor/outer loadings represent the correlation between each observed item (e.g., ECO1, SOC2) and its corresponding latent construct (e.g., economic factors, social factors). According to the literature, these factor loadings should be higher than 0.70, which is considered strong and indicates that the item is a reliable measure of the construct [52]. In this study, all the items meet this benchmark, confirming their validity, except for ECO3, which falls below this threshold with a value of 0.665, though it is still acceptable in exploratory research such as this study.

Table 2. Analysis for reliability and convergent validity

Latent Variables	Items	Factor Loadings	Composite Reliability (CR)	Cronbach's Alpha	Cronbach's Alpha
			Exogenous Construct		
Economic	ECO1	0.837	0.662	0.65	0.587
	ECO2	0.787			
	ECO3	0.665			
Social	SOC1	0.887	0.822	0.82	0.736
	SOC2	0.833			
	SOC3	0.852			
Personal	PER1	0.916	0.857	0.81	0.72
	PER2	0.774			
	PER3	0.849			
Technology	TECH1	0.795	0.748	0.746	0.663
	TECH2	0.849			
	TECH3	0.799			
Work-Environment	WEF1	0.909	0.916	0.912	0.85
	WEF2	0.933			
	WEF3	0.924			
			Endogenous Construct		
Gig Economy	GIG1	0.861	0.806	0.804	0.718
	GIG2	0.845			
	GIG3	0.835			

Benchmark: Factor loadings ≥ 0.70, CR ≥ 0.70, Cronbach's Alpha CR ≥ 0.70, and AVE CR ≥ 0.50.

Regarding the reliability and convergent validity measurements, Table 2 presents the three key measurements: Composite Reliability (CR), Cronbach’s Alpha, and Average Variance Extracted (AVE). Composite Reliability (CR) measures the internal consistency of a construct, ensuring that its items consistently measure the same concept. The benchmark for CR is ≥ 0.70, while values between 0.60 and 0.70 are still acceptable for exploratory research [55, 56]. This study’s PLS-SEM model shows that most of the constructs meet the required threshold, confirming strong internal consistency. Work-Environment and Personal constructs have the highest CR values with 0.916 and 0.857, respectively, followed by Social (0.822), Gig Economy (0.806), and Technology (0.748). However, Economic Factors, with a CR of 0.662, are slightly below 0.70, which is still acceptable for exploratory research. Cronbach’s Alpha, which evaluates the internal consistency of items within a construct by assessing how closely related they are, has a standard according to the literature of ≥ 0.70 for good internal consistency [52]. Based on the results presented in Table 2, Cronbach’s Alpha values follow the same pattern as CR, where all the constructs meet the standard except for the Economic construct, which has a Cronbach’s Alpha value of 0.662. Finally, the Average Variance Extracted (AVE) measures the amount of variance captured by a construct relative to the variance due to measurement error. In other words, AVE ensures that the items collectively explain the construct they are intended to measure. The benchmark for AVE is ≥ 0.50, which indicates that the construct explains at least 50% of the variance in its items [52]. Overall, in this study, all constructs exceed the AVE threshold of 0.50, confirming that they explain a significant proportion of the variance in their items and validating the strong convergent validity of the measurement model.

For the discriminant validity, Table 3 presents the cross-loadings, which compare the loading of each item (presented in bold in Table 3) on its intended construct to its loadings on other constructs. Items should load higher on their corresponding construct than on others, with a substantial difference between the primary and cross-loadings [52, 55]. The study's results confirm strong discriminant validity across all constructs. All items consistently load highest on their respective constructs, demonstrating that the constructs are well-defined and solid, ensuring strong discriminant validity for the PLS-SEM measurement model in this study.

Table 3. Discriminant validity results from cross-loading

	Economic	Gig Economy	Personal	Social	Technology	Work-Environment
ECO1	**0.837**	0.371	0.417	0.218	0.193	0.379
ECO2	**0.787**	0.476	0.177	0.335	0.331	0.556
ECO3	**0.665**	0.489	0.567	0.494	0.273	0.234
GIG1	0.459	**0.861**	0.296	0.443	0.343	0.556
GIG2	0.561	**0.845**	0.603	0.41	0.271	0.409
GIG3	0.465	**0.835**	0.421	0.617	0.321	0.551
PER1	0.472	0.504	**0.916**	0.283	0.289	0.296
PER2	0.329	0.283	**0.774**	0.216	0.205	0.031
PER3	0.384	0.495	**0.849**	0.285	0.612	0.408
SOC1	0.44	0.509	0.276	**0.887**	0.229	0.539
SOC2	0.34	0.438	0.31	**0.833**	0.401	0.551
SOC3	0.382	0.555	0.218	**0.852**	0.275	0.411
TECH1	0.375	0.297	0.383	0.194	**0.795**	0.255
TECH2	0.231	0.313	0.39	0.308	**0.849**	0.236
TECH3	0.268	0.287	0.35	0.356	**0.799**	0.035
WEF1	0.516	0.537	0.313	0.444	0.198	**0.909**
WEF2	0.522	0.561	0.382	0.624	0.272	**0.933**
WEF3	0.438	0.55	0.201	0.538	0.127	**0.924**

Note: Bold values represent the loadings of items on their corresponding constructs.

Other measurements to assess the discriminant validity of the PLS-SEM measurement model are the Fornell-Larcker Criterion and Heterotrait-Monotrait Method (HTMT), which are presented in the following Table 4. The Fornell-Larcker Criterion evaluates whether a construct shares more variance with its items than with other constructs in the model, ensuring that the constructs are distinct and measure unique concepts. In Table 4, the diagonal values (in bold) represent the square root of AVE for each construct, while the off-diagonal values represent the correlations between constructs. Discriminant validity is achieved when the diagonal values are greater than the off-diagonal values in their respective rows and columns. According to this, the results confirm that all constructs in the model are well-defined. Each construct's diagonal value is greater than the off-diagonal values in its row and column, demonstrating that each construct is more strongly related to its items than to other constructs. The Heterotrait-Monotrait Ratio (HTMT) is a method used to assess discriminant validity in PLS-SEM by evaluating the similarity between constructs. The benchmark for HTMT is < 0.90 (in some literature < 0.85), indicating acceptable discriminant validity. Also, values exceeding 0.90 suggest a lack of discriminant validity, meaning constructs may overlap or measure similar concepts. In this study, the HTMT results demonstrate strong discriminant validity across all constructs. All HTMT values are below the benchmark of 0.90, ensuring that the constructs are distinct and measure unique aspects of the model.

Table 4. Discriminant validity using Fornell-Larcker Criterion & Heterotrait-Monotrait Method (HTMT)

	Economic	Gig Eco.	Personal	Social	Technology	Work-Environment
Economic	**0.766**	0.801	0.687	0.623	0.5	0.659
Gig Economy	0.586	**0.847**	0.614	0.713	0.476	0.697
Personal	0.473	0.526	**0.849**	0.376	0.558	0.351
Social	0.453	0.583	0.313	**0.858**	0.451	0.67
Technology	0.356	0.367	0.46	0.35	**0.814**	0.27
Work-Environment	0.534	0.596	0.327	0.585	0.218	**0.922**

Note: The diagonal and bold values represent the square root of each construct's AVE. Below the diagonal are the values representing the correlations between the constructs, and above the diagonal are the HTMT values.

4-2-2- Structural Model Analysis

The Structural Model Analysis focuses on evaluating the relationships between the constructs (latent variables) established in the measurement model. To assess the PLS-SEM structural model in this study, three main assessments were conducted, including Collinearity, Path Coefficient, and Predictive Relevance (R^2, f^2, and PLSpredict).

Starting with collinearity, this occurs when two or more items in a model are highly correlated, leading to redundancy. To assess collinearity, the study used the Variance Inflation Factor (VIF), which quantifies how much the variance of a coefficient is inflated due to multicollinearity. According to the literature, the benchmark for VIF is below 3, indicating no significant collinearity concerns. The results of the collinearity assessment, presented in Table 5, reveal that most items have VIF values below the threshold of 3, confirming no severe collinearity problems in this study's model. For example, within the Economic Factors construct, all items (ECO1 = 1.694, ECO2 = 1.314, ECO3 = 1.338) exhibit acceptable VIF values. Similarly, indicators for Social Factors (SOC1 = 2.097, SOC2 = 1.670, SOC3 = 1.888), Personal Factors (PER1 = 2.532, PER2 = 1.924, PER3 = 1.640), Technology (TECH1 = 1.423, TECH2 = 1.634, TECH3 = 1.476), and Gig Economy (GIG1 = 1.995, GIG2 = 1.775, GIG3 = 1.591) all of them fall below the threshold of 3, indicating no collinearity concerns. However, within the Work-Environment Factors construct, WEF2 (3.306) and WEF3 (3.237) slightly exceed the threshold, suggesting moderate collinearity for these two indicators.

Table 5. Collinearity assessment using Variance Inflation Factor (VIF)

Latent Variables	Items	VIF
Economic	ECO1	1.694
	ECO2	1.314
	ECO3	1.338
Social	SOC1	2.097
	SOC2	1.67
	SOC3	1.888
Personal	PER1	2.532
	PER2	1.924
	PER3	1.64
Technology	TECH1	1.423
	TECH2	1.634
	TECH3	1.476
Work-Environment	WEF1	2.839
	WEF2	3.306
	WEF3	3.237
Gig Economy	GIG1	1.995
	GIG2	1.775
	GIG3	1.591

Benchmark: VIF < 3.00.

The second approach to analyzing and assessing the PLS-SEM structural model in this study is through Path Coefficient (β) analysis. The path coefficient measures the strength and direction of the relationship between constructs in the structural model. Although there is no strict threshold for β, values closer to 1 indicate stronger relationships. In the following Figure 5, which presents the Path Coefficient (β), we observe that, from the perspective of factors influencing the perception of the gig economy in Mongolia, the most influential constructs in the model are the social factors and personal factors, with path coefficient values of 0.254 and 0.251, respectively. Social factors showed a relatively strong positive influence ($\beta = 0.254$) on gig economy perceptions, indicating that community acceptance, encouragement from friends and family, and overall societal attitudes significantly shape how Mongolians view gig work. This result is aligned with Mongolia's collectivist cultural tendencies, where social endorsement plays a critical role in legitimizing alternative employment forms such as gig work. Personal factors also demonstrated a notable positive influence ($\beta = 0.251$), highlighting that individual lifestyle preferences, flexibility needs, and skills alignment are important drivers of positive attitudes toward gig work. This suggests that Mongolian participants who perceive gig work as fitting their personal schedules, goals, and abilities are more likely to view it favourably. The strong role of personal factors also reflects the growing desire among Mongolians, particularly younger generations, for autonomy and flexible employment opportunities. Closely following were work environment factors (β = 0.247), indicating that the conditions under which gig work is performed (e.g., platform fairness, stability, and growth opportunities) are also important but slightly secondary to the influence of social and personal alignment. Interestingly, economic factors (β = 0.207), though relevant, had less impact than expected. This suggests that while income generation and cost-efficiency are motivators, they may not be the dominant frame through which Mongolian participants evaluate gig work, possibly because of competing concerns like job dignity, autonomy, or community perception.

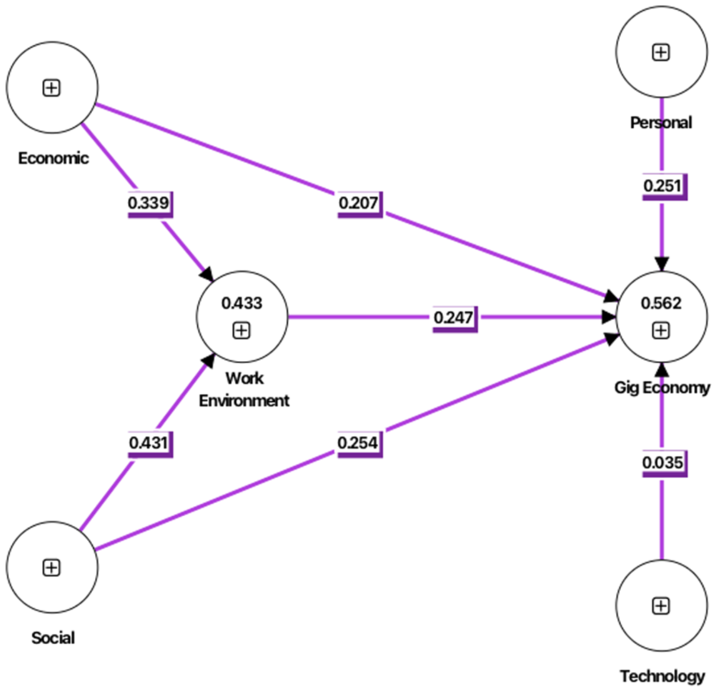

Figure 5. Structural model

Notably, technological factors (β = 0.035) had the weakest influence on perception. This is a striking result considering that gig work is largely digital in nature. It may reflect a broader reality in Mongolia: although platform usage is increasing, digital infrastructure, literacy, and trust in digital systems remain uneven, particularly in non-urban areas. The low influence of technology in perception formation likely points to gig economy awareness and evaluation being socially mediated rather than technology-driven at this stage of adoption. Regarding the other perspective of the structural model, which evaluates the relationship between economic and social factors and their effect on the gig economy as a work environment in Mongolia, social factors (β = 0.431) are shown to have a stronger influence on the gig economy work environment than economic factors (β = 0.339). This reinforces the interpretation that Mongolian participants evaluate gig work not only through practical financial benefits, but also through the lens of social meaning and acceptability. Therefore, in Mongolia, the ability of gig platforms to gain traction depends as much on their integration into everyday social narratives as on their economic attractiveness.

Regarding the hypothesis test, the results in Table 6 indicate that some hypotheses are supported, while others are not, based on the statistical significance (p-value ≤ 0.05) and the direction of the Path Coefficient (β). For H1, which posits that economic factors positively influence the perception of the gig economy, the hypothesis is supported as the path coefficient (β = 0.207) is positive and statistically significant (p = 0.014). However, H1a, which hypothesizes that economic factors positively influence the gig economy as a work environment, is not supported because, despite a positive β value (0.339), the p-value (0.069) is greater than 0.05, indicating no statistical significance. For H2, which suggests that social factors positively influence the perception of the gig economy, the hypothesis is not supported due to a lack of statistical significance (p = 0.111) despite a positive β value (0.254). On the other hand, H2a, which examines the influence of social factors on the gig economy as a work environment, is supported as the β value (0.431) is positive and the p-value (0.023) is below the significance threshold. H3, which posits that technological factors positively influence the perception of the gig economy, is supported with a β value of 0.035 and a p-value of 0.042, indicating statistical significance. However, the effect is weak due to the low β value. For H4, which suggests that personal factors positively influence the perception of the gig economy, the hypothesis is not supported as the p-value (0.116) exceeds 0.05, despite a positive β value (0.251). Finally, H5, which hypothesizes that work-environment factors positively influence the perception of the gig economy, is supported with a β value of 0.247 and a statistically significant p-value of 0.008.

Table 6. Results of hypotheses testing

Hypothesis	Hypothesis Path	Path Coefficient (β)	STDEV	T statistics	p-values	Interpretation
H1	ECO → GIG	0.207	0.09	2.3	0.014*	Supported
H1a	ECO → WEF	0.339	0.186	1.822	0.069	Not Supported
H2	SOC → GIG	0.254	0.159	1.592	0.111	Not Supported
H2a	SOC → WEF	0.431	0.189	2.279	0.023*	Supported
H3	TECH → GIG	0.035	0.017	2.047	0.042*	Supported
H4	PER → GIG	0.251	0.16	1.571	0.116	Not Supported
H5	WEF → GIG	0.247	0.063	3.921	0.008**	Supported

Note: STDEV: Standard Deviation; $^{**}p \leq 0.01$, $^{*}p \leq 0.05$.

Regarding the strength of the PLS-SEM structural model in this study, the results of the R^2 values indicate that the model provides a moderate-to-strong explanation of the variance in both constructs. For the main endogenous construct, the Gig Economy, the R^2 value is 0.562, meaning that 56.2% of the variance in the perception of the gig economy is explained by the predictors in the model, including economic, social, technological, personal, and work-environment factors. For Work Environment, the R^2 value is 0.433, indicating that 43.3% of the variance in the perception of the gig economy as a work environment is explained by its predictors, such as economic and social factors. The results of these R^2 values can be found in Appendix (A1).

The f^2 values in the model measure the effect size of each exogenous construct on the endogenous constructs, reflecting how much an independent variable contributes to explaining the variance of a dependent variable. According to the benchmark for f^2 values, 0.02 - 0.15 indicates a small effect, 0.15 - 0.35 is a medium effect, and ≥ 0.35 is a large effect. In this model, SOC → WEF has the largest f^2 value (0.261), representing a medium-to-large effect and demonstrating that social factors significantly contribute to explaining the variance in the Work Environment. Similarly, ECO → WEF shows a medium effect with an f^2 value of 0.161. Other relationships, such as PER → GIG (0.097), SOC → GIG (0.087), WEF → GIG (0.078), and ECO → GIG (0.058), exhibit small effect sizes, indicating that these predictors play minor but meaningful roles in shaping perceptions of the gig economy in Mongolia. In contrast, the relationship TECH → GIG has a negligible effect (0.002), highlighting that technological factors contribute minimally to the variance in the perception of the gig economy. The results of these f^2 values can be found in Appendix (A2).

Finally, the PLS-SEM predictive performance comparison with the Linear Model (LM), as presented in Appendix (A3), assesses the predictive accuracy of the PLS-SEM model against the LM using two common error metrics: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The results reveal that, for both constructs, Gig Economy (GIG) and Work Environment Factors (WEF), the PLS-SEM model consistently outperforms the LM in predictive accuracy. Specifically, the RMSE values for PLS-SEM are lower than those for LM across all indicators, indicating better predictive performance (e.g., GIG1: PLS-SEM RMSE = 0.736 vs. LM RMSE = 0.971). Similarly, the MAE values for PLS-SEM are also consistently lower than those for LM, reinforcing the superior accuracy of the PLS-SEM model (e.g., GIG2: PLS-SEM MAE = 0.549 vs. LM MAE = 0.708). These results highlight that the PLS-SEM model in this study provides a more precise prediction of the items in both constructs compared to the traditional linear model.

5- Discussion

The findings of this study provide valuable insights into the factors influencing perceptions of the gig economy in Mongolia and the relationship between these factors and the gig economy as a work environment. The results demonstrate that social factors, economic factors, personal factors, and work-environment factors have varying levels of direct and indirect effects on perceptions of the gig economy, while technological factors exhibit negligible influence. As an example, social factors emerged as one of the most significant predictors of perceptions of the gig economy and its role as a work environment, with a path coefficient of 0.254 for SOC → Gig Economy and 0.431 for SOC → Work Environment. This finding highlights the importance of social acceptance and community support in shaping perceptions of gig work in Mongolia. This result lies in Mongolia's communal culture, where collective attitudes and social norms heavily influence individual decisions. In such a society with cohesive communities, the endorsement of gig work by social circles can enhance its legitimacy and perceived value. To further foster a gig economy culture in Mongolia, strengthening community-level awareness campaigns and promoting positive narratives around gig work could be highly effective.

Moreover, personal factors emerged as the second most influential predictor of perceptions of the gig economy in Mongolia, with a path coefficient of β = 0.251. This result highlights the importance of individual preferences and lifestyle alignment in shaping attitudes toward gig work. In Mongolia, the flexibility offered by gig work aligns well with the needs of individuals seeking to balance work and personal commitments, particularly younger generations who prioritize adaptable work schedules. Additionally, gig work provides opportunities for individuals to leverage their unique skills, making it an attractive option for those seeking autonomy in their employment choices. However, despite its positive influence, the gig economy's appeal may be limited by concerns about job stability and long-term career growth. These concerns are especially relevant in Mongolia, where formal employment opportunities are often scarce, and individuals may view gig work as a short-term solution rather than a sustainable career path.

The work-environment factors showed the third strongest influence on perceptions of the gig economy ($\beta = 0.247$) and were significantly influenced by social factors ($\beta = 0.431$) and economic factors ($\beta = 0.339$). This highlights the role of a supportive work environment in bridging the gap between the social and economic dimensions of gig work. For Mongolia, where the gig economy is still nascent, the perception of a secure and growth-oriented work environment likely resonates with individuals seeking long-term opportunities beyond temporary or precarious jobs. Moreover, the economic factors showed a moderate but meaningful influence on both the perception of the gig economy ($\beta = 0.207$) and its role as a work environment ($\beta = 0.339$). This reflects Mongolia's evolving economy, where gig work provides a much-needed supplemental income for many individuals. Despite its economic benefits, gig work in Mongolia is often associated with low pay and income instability. A lack of worker protections, such as minimum wage guarantees or benefits, may explain why economic factors have a moderate rather than strong influence (e.g., social factors) on perceptions.

Interestingly, technological factors demonstrated the weakest influence on perceptions of the gig economy in Mongolia, with a path coefficient of $\beta = 0.035$, indicating a negligible impact. This result suggests that technology plays a minimal role in shaping attitudes toward gig work, which can be attributed to many factors in Mongolia. One main factor is the digital divide, while urban areas like Ulaanbaatar enjoy relatively high internet penetration and access to digital platforms, rural regions face significant barriers due to limited connectivity and digital literacy. According to the International Telecommunication Union, internet penetration in Mongolia is around 70%, but disparities between urban and rural areas remain significant. Furthermore, the reliance on informal systems, such as word-of-mouth arrangements, diminishes the perceived importance of technology in accessing gig work. Many Mongolians, especially in rural areas, may not rely on digital platforms to find or engage in gig work, reducing the influence of technological factors on their perceptions. This lack of reliance on digital tools highlights the need for bridging the gap in technological access and training to enhance the role of technology in the gig economy.

6- Conclusion

This study provides valuable insights into the factors influencing perceptions of the gig economy in Mongolia and the interplay between these factors and the gig economy as a work environment. Using a PLS-SEM approach, the findings reveal that social, economic, personal, and work-environment factors significantly shape perceptions of the gig economy, while technological factors have a negligible influence. Social factors emerged as the strongest predictor, emphasizing the importance of social acceptance and community support in fostering positive perceptions of gig work. Economic factors and personal factors also played substantial roles, reflecting the critical influence of financial stability, lifestyle alignment, and individual preferences. The work-environment factors further acted as a mediator, bridging the economic and social dimensions of the gig economy, while the minimal impact of technological factors highlights the need to address Mongolia's digital divide.

While this research provides critical insights, several limitations should be acknowledged. First, the study focuses exclusively on Mongolia, which limits the generalizability of the findings to other contexts. Future research could compare these results with studies conducted in other developing or developed countries to identify cross-contextual patterns and differences. Second, the study does not account for the influence of external macroeconomic or political factors, such as government regulations, economic shocks, or global trends in the gig economy. These factors could have a significant impact on perceptions and adoption of gig work, but were not addressed in this research, as it is hard to collect the data related to them. Third, while the PLS-SEM methodology provides robust insights into the relationships between constructs, it does not explore causal relationships or dynamic interactions over time. Integrating complementary methods, such as experiments or system dynamics modelling, could provide deeper insights into causal mechanisms. Finally, the study's exclusive focus on worker perceptions leaves out the perspectives of other key stakeholders, such as gig platform operators, policymakers, and employers. Including these perspectives in future research could offer a more holistic understanding of the gig economy's ecosystem and the factors that influence its development.

Building on the findings and limitations of this study, future research should explore several critical areas to deepen our understanding of the gig economy and its dynamics. First, the relatively small sample size of 43 participants. While this was influenced by contextual factors such as limited digital access, informal gig participation, and cultural sensitivities in Mongolia, it may affect the generalizability of the findings. Future research could expand the sample size and target a broader range of participants across different regions and occupational categories to validate and extend the insights gained from this exploratory study. Second, cross-cultural comparisons could provide valuable insights by identifying similarities and differences in perceptions of the gig economy across countries. Such studies would consider varying cultural, economic, and technological contexts, offering a broader understanding of how local conditions shape gig work perceptions. Third, the digital divide and technological integration warrant closer examination. Investigating the role of digital infrastructure and literacy in influencing the adoption and perception of gig work, particularly in rural or underserved areas, could help address barriers to gig economy participation. Additionally, future research should analyze policy and institutional factors, such as government policies, labor regulations, and institutional frameworks, to understand their impact on the growth and perception of the gig economy in developing economies like Mongolia. These factors could significantly shape the sustainability and inclusivity of gig work. Employing longitudinal studies would also be beneficial, as they allow researchers to track changes in perceptions of the gig economy over time. Such designs could uncover how economic, social, or technological shifts influence attitudes and adoption trends. Another limitation of this study is the restricted occupational diversity within the sample. Although efforts were made to recruit participants from across Mongolia, most respondents were from urban areas and represented more digitally connected segments of the workforce. Informal or platform-based gig workers in rural areas were underrepresented due to access barriers, digital literacy challenges, and the hidden nature of many informal gig activities. This limitation may affect the generalizability of the findings across all segments of Mongolia's gig economy. Future research should specifically target a broader range of occupational categories, particularly those in rural and semi-urban settings, to capture a more comprehensive and representative understanding of gig economy perceptions. Finally, platform-specific studies could examine the differences between gig platforms to understand how their policies, reputation, and working conditions impact worker engagement and perception. This would provide a nuanced view of how individual platforms contribute to the broader gig economy landscape.

7- Declarations

7-1- Author Contributions

Conceptualization, AB. and Z.L.; methodology, A.B.; software, A.B.; validation, A.B. and Z.L.; formal analysis, A.B.; investigation, A.B.; resources, A.B.; data curation, A.B.; writing—original draft preparation, A.B.; writing—review and editing, A.B.; visualization, A.B.; supervision, Z.L.; project administration, Z.L.; funding acquisition, Z.L. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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