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Mapping the prestige and social value of occupations in the digital economy

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ABSTRACT

With the emergence of the digital economy, the occupational landscape in many countries has undergone major transformations. While scholars have started to study the working conditions of digital economy occupations such as app-based food delivery couriers and social media influencers, assessing societal perceptions of these occupations remains uncharted territory. This article provides a substantive contribution through an in-depth analysis of occupational prestige and occupational social value perceptions across 76 UK digital economy occupations. Leveraging two expansive surveys with more than 2400 respondents, the findings show that these nascent occupations tend to have modest prestige, and that their perceived social value is lower than that of analogous non-digital occupations. Socio-economic factors and attitudes foster variability in societal perceptions. The research thus advances a nuanced understanding of the evolving digital economy, providing evidence for fellow researchers, policymakers, and the larger public, for whom the results help contextualize career choices and occupational identities.

1. Introduction

As the digital transformation continues to mature, the integration of novel digital technologies has resulted in the emergence of many new occupations (Kane, 2017). From cryptocurrency miners to artificial intelligence (AI) consultants and app-based food delivery couriers, the digital economy[1] is expanding with forms of work that would have been incomprehensible even one generation ago. Whether new occupations ensure that digital technologies function or capitalise on such technologies, the ongoing occupational change has become a topic of growing importance. This change is reflected in the dynamism of the digital economy. While comprehensive data is scarce, sector-specific indicators show the fast growth of individual digital economy occupations, a trend projected to continue in the years to come. The Online Labour Index, for example, tracks the supply and demand of online freelancing tasks over time, thus giving a rough indication of the prevalence of online freelancing occupations (Online Labour Observatory, 2023). Compared to the normed baseline value of 100 when the measurement started in June 2016, the index is at 140 in mid-March 2024, highlighting dynamic growth. According to the US Bureau of Labor Statistics (2023), the "projected percent change in employment" from 2021 to 2031 for Software Developers, Quality Assurance Analysts, and Testers occupations is 25 %, indicating much faster growth than average. These two examples show the societal relevance and future importance of digital economy occupations.

Although the success of organisational change regarding digital technologies relies on internal acceptance, some occupations can transform for the worse. Dynamic occupational transformations that come with the introduction of new technologies may result in the obsolescence of some tasks and skill sets, meaning that certain employees struggle with job insecurity and lowered employability. For example, automation and AI streamline processes that once required extensive human intervention, such as data entry, leading to reduced demand for clerical positions (Frey & Osborne, 2017). In the area of social media, the phenomenon of aspirational labour is common, where individuals engage in unpaid or badly paid work, which often is emotionally taxing, in the hope of uncertain future returns (Duffy, 2016). Compared to earlier, digital economy occupations in the creative

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[1] We follow conceptualizations of the digital economy that understand it as consisting of work and occupations which are heavily enabled by the Internet or take place on digital platforms (Baiyere et al., 2023; Foster, 2020; Newlands, 2022a). The digital economy thus includes emerging occupations that happen primarily on the Internet (e.g., social media occupations) or whose work process is substantially shaped by Internet-enabled technologies such as mobile cartography and GPS-tracking (e.g., ride-hailing and food delivery).

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industries (e.g., online freelance writers, digital journalists) face stronger self-branding pressures (Blyth et al., 2022). Finally, the rise of the gig economy, while offering flexibility, has also seen a proliferation of precarious working conditions, with occupations such as app-based ride-hail drivers or app-based food delivery couriers facing job instability, a lack of benefits, and strong platform dependence as well as algorithmic control (Möhlmann et al., 2021; Newlands, 2022a, 2022b; Schor et al., 2020; Van Doorn, 2020). These examples show how technological changes in the workplace can affect employee wellbeing, with studies into the digital economy addressing fundamental questions of job quality such as working standards, labour processes, and pay (Chen & Sun, 2020; Gillespie, 2020; Hornuf & Vrankar, 2022; Tubaro et al., 2020; Van Doorn, 2020). However, job quality is a multidimensional concept and cannot be distilled into a single aspect (Findlay et al., 2013). One important, though under-researched, dimension of job quality is the societal perception of an occupation (Newlands & Lutz, 2024).

Such perceptions can impact someone's self-esteem and sense of worth (Lamont, 2012; Petriglieri et al., 2019). Indeed, research has shown that workers in the digital economy face identity issues due to not getting the social recognition they deserve (Healy et al., 2020; Newlands, 2022a; Phung et al., 2021). Given their novelty, these occupations have not had the time to build up legitimacy or a reputational consensus, compared with established occupations such as plumbers or accountants. An occupation's reputation is also important in shaping self-selection during recruitment processes, where some individuals choose their occupations based on its prestige or perceived social value (Burke, 2017; Kleinjans et al., 2017). Many young people, for instance, undertake work in the digital economy out of a desire for the cultural cachet of working in social media, fintech, or tech start-ups (Newlands & Fieseler, 2020; Shigihara, 2018). However, many also seek work in these new occupations out of necessity, where the often informal and more immediate income of online freelancing or gig work can offer a source of income to those with few alternative options (Newlands, 2022b; Van Doorn, 2020).

Currently, we have little knowledge of how digital economy occupations are socially evaluated. External evaluations of occupations can capture different aspects such as occupational prestige (OP) and occupational social value (OSV). The former is an established construct in occupational research (e.g., Treiman, 1977), while the latter has gained increasing attention, especially with the notion of 'Bullshit Jobs' that emerged around Graeber's (2018) influential contribution. OP addresses the status or reputation of an occupation in society, whereas OSV describes its perceived usefulness. We address this knowledge gap by studying social perceptions of the digital economy, broadly speaking, including occupations in social media, online freelancing, the gig economy, and the AI and IT industry. Beyond investigating OP and OSV in isolation, we also assess intersection of the two, showing value tensions and legitimization dynamics. Thus, our research provides a novel perspective to social stratification research as well as scholarship on the digital economy, with implications for different stakeholders such as policymakers, managers and those working in the digital economy themselves.

The paper has three research objectives: a) assess the occupational prestige and occupational social value hierarchy of digital economy occupations b) contrast the occupational prestige and occupational social value of digital economy occupations with comparable non-digital economy occupations c) explore differences in the OP and OSV of digital economy occupations based on demographic and attitudinal characteristics.

To address these research objectives, we examine digital economy occupations in terms of both OP and OSV in two distinct indices, so that we observe where they differ or overlap rather than assuming that they are interchangeable. Using a representative sample of over 2400 respondents, we offer two new indices of the OP and OSV of 76 digital economy occupations in the UK. We also investigate the social structuration of OP and OSV. The findings indicate that digital economy occupations, with some exceptions, are perceived as inferior in OSV to comparable non-digital economy occupations, pointing to legitimization challenges. More public-facing and aspirational digital economy occupations, such as those in social media, are seen as not prestigious and of limited social value, whereas more 'foundational' back-end occupations (e.g., software development) accrue better evaluations. We also show how digital economy occupations are more favourably assessed among ethnic minorities and younger adults.

2. Literature review

The literature review section is structured into two parts. In the first part, we discuss literature on the societal perceptions of digital economy occupations (2.1). No study has mapped such perceptions comprehensively. Instead, the literature on specific digital economy occupations is scattered across disciplines, including business/management research, the sociology of work, industrial relations, communication and media studies, critical data studies, and tourism and hospitality research. Most of this literature captures the perceptions of people working in these occupations themselves, with limited research on external perceptions. To structure the complex literature on digital economy occupations, and to guide the empirical analysis, we categorize the 76 occupations into nine relatively distinct groups (see more information on this categorization later in the article): Gig Economy Occupations; Online Freelancing Occupations; Social Media Occupations; Fintech Occupations; Data Entry, Validation and Trading Occupations; Digital Development and Design Occupations; IT Professionals Occupations; Digital Marketing and Sales Occupations; and Technology Entrepreneurship Occupations. We will go through each of these occupation groups in turn in the first part of the literature review. The second part of the literature review (2.2.) contains a concise discussion of the two key axes of external evaluation of occupations that we then assessed empirically: prestige and social value (Newlands & Lutz, 2024). We describe existing measurement attempts of OP and disentangle why OP and OSV should be separated.

2.1. Societal perspectives of digital economy occupations

Societal perceptions of *Gig Economy* occupations have been predominantly negative because of media portrayals and ongoing regulatory battles (Geissinger et al., 2021; Newlands, 2021b). Driving such negative perceptions are the low entry barriers, tough working conditions, and a high proportion of migrant workers (Van Doorn, 2020). Phung et al. (2021), for example, discussed the 'social taint' of Uber drivers. While gig economy occupations, such as App-Based Ride-Hail Driver and App-Based Food Delivery Courier, provide accessible labour opportunities, research demonstrates that both workers (Ashford et al., 2018) and customers (Healy et al., 2020) perceive gig economy occupations as career dead-ends. Some food-delivery couriers even sought to hide gig economy experiences on their CVs due to the perceived low prestige of the work (Newlands, 2022b). However, many undertake such work because alternative labour opportunities are even less desirable (Barratt et al., 2020). It is thus important to understand the potentially discordant perspectives of these occupations.

Occupations in *Online Freelancing* are primarily done through online labour platforms such as Upwork (Blyth et al., 2022; Kässi & Lehdonvirta, 2018; Tóth et al., 2022; Wood et al., 2018). Ranging from Online Freelance Writers to Online Freelance Personal Assistants, such occupations can involve low-skill repetitive tasks as well as creative knowledge work (Gandini, 2016; Howcroft & Bergvall-Kåreborn, 2019). However, there are often high income disparities between those who are successful in obtaining clients and those who are not, exacerbated by global competition (Popiel, 2017; Sutherland et al., 2019). A growing body of research has investigated how online freelancers create occupational self-identities through cultivating connections and self-branding activities directed at potential clients (Blyth et al., 2022;

Petriglieri et al., 2019). Such workers are highly concerned with how they are perceived, particularly as positive external evaluations can garner higher rates of pay (Demirel et al., 2021). However, there has been a dearth of research assessing how these occupations are viewed.

Many *Social Media* occupations such as Beauty Bloggers and Social Media Travel Influencers are similarly concerned with external perceptions and the development of their 'brand', particularly since they monetise their labour through building an audience and becoming a form of micro-celebrity (Mardon et al., 2018). Dependent on unpaid 'aspirational labour', the economic rewards can be extremely uneven and success can require workers to consistently create content across multiple different online platforms (Duffy, 2016; Scolere et al., 2018). Research suggests that these occupations are seen as highly desirable among young people (Newlands & Fieseler, 2020), but are not necessarily considered to be long-term or sustainable careers (Cotter, 2019). On the other hand, more back-end social media occupations such as Online Content Moderators and Social Media Community Managers are far less visible, less entrepreneurial, and with work tasks that can be highly distressing (Gillespie, 2020).

Although *Fintech* occupations have yet to develop coherent societal reputations, there seems to be a rough demographic homogeneity among those undertaking Fintech work. Online Stock Traders and Cryptocurrency Traders (e.g., Bitcoin), for example, are predominantly white, well-educated, and male (Caliskan, 2022; Steinmetz et al., 2021). If and how this impacts the perception of such occupations remains to be seen, but as fintech becomes more mainstream and attracts a young, well-educated demographic, it is an important research question whether and how societal perceptions of the work differ from those aspiring towards it.

Occupations in *Data Entry, Validation and Trading*, in contrast to several of the occupations already mentioned, form a critical infrastructural component of the digital economy (Bechmann & Bowker, 2019). Operating at the back end and underpinning the development of AI and other data-intensive technologies, occupations such as AI Trainer, Online Microworker and Digital Image Labeler are relatively nascent. Data preparation work remains under-the-radar in terms of the public consciousness (Newlands, 2021a; Tubaro, 2021) and its often 'invisible' nature has invited Gray and Suri (2019) to refer to it as 'ghost work'. However, in contrast to the public invisibility, these occupations have attracted a steady stream of scholarly research into the low pay and poor working conditions (Miceli et al., 2020; Newlands & Lutz, 2021; Tubaro & Casilli, 2019). Although an ongoing debate persists about whether such work will be replaced by automation (Tubaro et al., 2020), even if many such occupations are replaced the question remains of how they are currently evaluated.

Similarly infrastructural, occupations in *Digital Development and Design* underpin the functioning of the digital economy. These can include highly technical positions such as Computer Scientist and Software Developer, as well as Mobile App Programmers and Video Game Designers. Verma et al. (2022), for instance, show that employers put more emphasis on technical skills in AI related positions. While closely intertwined with data-work, these development and design occupations tend to be more desirable. As Sambasivan et al. (2021) explain, 'everyone wants to do the model work, not the data work'. However, current research also shows that software production can be exclusionary towards women (Tassabehji et al., 2021) and still precarious (Bergvall-Kåreborn & Howcroft, 2013). There has been limited research on the social evaluations of such occupations, though the US General Social Survey included five comparable titles, which had a high level of perceived 'social standing' (Smith & Son, 2014).

IT Professionals, such as Data Protection Lawyer, AI Consultant and IT Manager, are high-skill and high-income occupations (Orr & Davis, 2020). Aligning closely with more traditional occupations, these tend to involve managerial responsibilities or professional training with the expectation that they would garner higher levels of prestige. This perception is borne out through the inclusion of comparable occupation titles in the 2012 US General Social Survey, where all similar titles had high 'social standing' scores (Smith and Son, 2014).

Taking a broader perspective on the digital economy, we can also observe a growing number of occupations in *Digital Marketing and Sales*, such as E-Commerce Manager and Social Media Marketing Manager (Shawky et al., 2020). Given how the UK is a highly service-driven economy, this growing segment is of particular importance to examine, even though there remains limited research on how these occupations are perceived. We may, however, expect to observe a difference between the back-end technical roles compared to consumer-facing service roles, such as the Chatbot Operators or Email Marketers which may be perceived as lower-end and lower-skilled work (Huang & Rust, 2018; Newlands, 2021a).

As a final segment of the digital economy, many *Technology Entrepreneurs and Vendors* have emerged at both the high-end and the low-end of the digital economy. Research into digital start-up founders shows that some have thrived, earning extensive amounts of money and would be expected to garner high societal evaluations (Kraus et al., 2019). This is also evident from the highly scored Owner of a Computer Software Company occupation title in the 2012 US General Social Survey (Smith & Son, 2014). However, the vast majority of such entrepreneurs operate on a small scale, utilising online platforms such as eBay or Alibaba for small-scale e-commerce (Zhang, 2020). Research into Airbnb Hosts, for example, has shown that people have mixed perceptions of the social impact of such short-term rental platforms, and the reputation of the platform can impact the legitimacy of the occupation (Miguel et al., 2022; Newlands & Lutz, 2020).

2.2. Occupational prestige and occupational social value

We draw explicitly on the long-standing research tradition of measuring OP through survey research, which aims to tap into the societal collective consciousness (Zhou, 2005). OP, unlike other measures of social stratification such as income or education that can be drawn from registry data, captures aggregate societal evaluations and perceptions (i.e., a collective sentiment of the status of a certain occupation). Therefore, generalizable survey data is the most apparent and conventional approach to measure OP. Accordingly, since the first major study by the US National Opinion Research Centre in 1947, OP has been primarily assessed by surveys. Later replications of this study, such as those conducted in 1964 and 1989, were joined by Treiman's (1977) aggregated Standard International Occupational Prestige Scale, to situate OP as a key sociological concept. Most recently, the 2012 US General Social Survey (Smith and Son, 2014) offers one of the most updated and extensive measurements of OP.

These surveys, however, lack a holistic set of OP measurements for digital economy occupations. In the 2012 US General Social Survey, for example, prestige scores are provided for occupations such as 'Saloonkeeper' and 'Organizer for a Religious Crusade', but there is no such similar provision for emerging occupations such as 'Social Media Manager', 'Data Broker' or any of the array of occupations found in the gig economy. The few relevant occupation titles were mostly related to computer-related roles. Reminiscent of a rear-view mirror, these lists thus provide a glimpse into the occupational landscape of the past but are not fit-for-purpose to assess the modern digital economy. As such, we respond to the call by De Camargo and Whiley (2020) who argue for more nuanced research into prestige not only reflective of the fluidity of the concept, but also directly addressing the need to assess the prestige of new occupations.

Studies of OP have also been inconsistent in their measurement protocols by using different wording but claiming to be measurements of prestige. The 2012 US General Social Survey, for instance, asked respondents to rank occupations based on their 'social standing', rather than directly on prestige (Smith and Son, 2014). Ulfsdotter Eriksson and Nordlander (2022) in their study assess occupations using the phrase 'how it is valued in society with regards to status'. The Goldthorpe and

Hope (1974) scale similarly enquired about occupations' 'value to society'. Because of this conflation, it was important to directly ask about the prestige of digital economy occupations in our study.

Given the growing interest in the social value of occupations, we also separately assessed the social value of digital economy occupations, rather than conflate the two concepts. Research has shown that people are interested in doing work that is useful to society (Wolfe & Patel, 2019), and that perceived job usefulness is associated with life satisfaction and individual motivation (Allan et al., 2018). Work meaningfulness, usually assessed through individual-level items, is a significant feature of work, and usually described as the 'degree to which the employee experiences the job as one which is generally meaningful, valuable, and worthwhile' (Hackman & Oldham, 1975, p. 162). Williams et al. (2022), for example, refer to 'work significance', which is the perceived usefulness both to the production process and to society. They find that those in routine and manual occupations are less likely to report that their job is useful to society and that more respondents think that their job is useful to their organisation than to society. This is distinct, yet related, to task significance which is workers' sense that what they do is beneficial to society (Grant, 2008).

Interest in the social value of occupations has also increased since David Graeber's (2018) exposition on seemingly pointless 'Bullshit Jobs', even though Soffia et al. (2022) contradict Graeber's (2018) key claims by showing that the proportion of workers describing their work as useless is low and in fact declining (c.f. Dur & Van Lent, 2019). Soffia et al. (2022) instead argue that the feeling of uselessness is a symptom of bad management and a toxic workplace culture. By contrast, Walo (2023), in a recent article with US data, found evidence for parts of Graeber's (2018) bullshit jobs theory. Specifically, occupations which are perceived as useless, by those working in these occupations themselves (rather than by broader social consensus), cluster in certain sectors such as sales and administrative support. However, in line with Soffia et al. (2022), the author also identifies other aspects that predict the uselessness of occupations such as 'alienation, social interaction and public service motivation' (p. 19). In our study we decided to assess OP and OSV as distinct to create a holistic overview of the social evaluation of digital economy occupations in the UK.

While aiming to garner aggregate evaluations, we also approach this study from the premise that such evaluations are dynamic and variable (Avent-Holt et al., 2020). Social narratives about specific occupations are usually derived from interactional experiences, socialisation processes and media coverage (Alvesson et al., 2008). Individuals also evaluate occupations based on numerous criteria, both consciously and subconsciously (Freeland & Hoey, 2018; Lynn & Ellerbach, 2017; Valentino, 2020), such as perceived education requirements, economic rewards, exclusivity or occupational closure (Lissitsa et al., 2017; Mejia et al., 2021). Gender- and racially-segregated occupations, as well as those with high levels of economic renumeration are also perceived as being more prestigious (Freeland & Hoey, 2018; Valentino, 2020, 2022; Zhou, 2005). Thus, individuals might vary in how they evaluate occupations in significant ways. Sociological research has also shown that individuals differ in their evaluations based on their own socio-demographic and attitudinal factors. Zhou (2005), for instance, identified that race, educational attainment, and gender impact how an individual rates OP. Lynn and Ellerbach (2017) also identified that the level of education influences the consensus that individuals reach around OP. Accordingly, we decided to explore whether there is significant variation in how individuals evaluate digital economy occupations based on socio-demographic and attitudinal factors.

3. Methods

3.1. Occupation list

The list of digital economy occupation titles was derived based on the authors' expertise and extensive background research, including peer consultation with researchers in the area and reliance on established taxonomies such as the online labor index (Kässi & Lehdonvirta, 2018). A pre-test in the form of a brainstorming task further assured the completeness of the list. Specifically, in December 2021 we asked 50 responses (UK residents, equal sex proportion, Prolific) to list as many digital economy occupations as possible in a large open text box. We offered a short definition of the digital economy (*'The digital economy refers to new forms of work enabled by the Internet.'*) but kept the question purposefully open to allow for maximum brainstorming. The overwhelming majority of occupations listed was already in our list, but the responses resulted in the addition of two occupation titles: Online Freelance Tutor and Online Freelance Therapist. Our approach resulted in 76 digital economy occupations across the nine groups mentioned. The boundaries between some digital economy occupations are fluid and many of these occupations lack the strong institutionalization of established occupations have (e.g., many digital economy occupations do not have strong professional bodies). Moreover, despite useful typologies (Duggan et al., 2020; Howcroft & Bergvall-Kåreborn, 2019; Vallas & Schor, 2020),[2] the fragmented academic literature does not fully cover the breadth and depth of these roles, so that devising a clear-cut categorization presents challenges. Despite this, our categorization into nine groups is the result of extensive deliberation and iterative refinement within the co-author team, representing a robust solution that aligns with existing digital economy literature (see Literature Review). Our categorization differentiates the occupations based on task nature, work modalities, technological contexts, and proximity within ISCO-08 unit groups (International Labour Organization, 2008). For example, Social Media Occupations are characterized by self-employment, public interaction, thus contrasting with Digital Marketing and Sales Occupations, which are more corporately structured and tend to focus on back-end operations.

The list of 76 digital economy occupations constitutes a sub-section of a larger list of 580 occupation titles developed by the authors (Gmyrek et al., 2024; Newlands & Lutz, 2024). The full list was aligned to ISCO-08, so that every ISCO-08 unit group is matched to at least one representative occupation title. As such, for each digital economy occupation we assigned a best-fit ISCO-08 unit group. Each occupation title has been given a unique ID code (e.g., NL001), distinct from the respective ISCO-08 unit group code for future cross-sample analysis. For robustness of the occupation list, we conducted a comprehension test to ensure that the occupations are broadly understandable by a British audience.[3] Table 1 displays these occupation titles and groups.

3.2. Measurement

3.2.1. Measurement of occupational prestige and Social value

To directly measure OP and OSV, we developed a new survey

[2] These typologies tend to cover the gig economy or platform work only but not the full spectrum of digital economy occupations.

[3] In December 2021, we collected 800 survey responses on Prolific to test the general comprehension of occupation titles. Participants were screened for an equal gender distribution (50% male, 50% female) and residence in the UK. The survey involved an open text task where respondents had to write what they thought someone with the specific occupation title does at work. The question prompt was: *'On the next page you will be provided with a list of 36 occupational titles. For each title, please write a short description of what you think somebody with this occupational title does at work. If you are unsure, please provide your best guess. If you have absolutely no idea at all what the occupational title refers to and cannot infer a potential description from the title, please write "I have no idea what this refers to".'* Open text responses were coded in Microsoft Excel as a binary of comprehension/no comprehension, with each occupation title receiving 50 responses. Occupation titles with below minimum acceptable comprehension (80%) were replaced, such as 'Tanner' (erroneously considered to be an operative of a tanning salon by most respondents) and 'Ambassador' (heavy conflation with a brand ambassador).

Table 1
Digital Economy Groups and Occupation Titles.

Digital Economy Group Number and Title	Occupation Titles in Group
1: Gig Economy (5 titles)	Online Freelance Care Worker (e.g., Care.com), App-Based Ride-Hail Driver (e.g., Uber), Online Freelance Domestic Cleaner (e.g., Helpling), E-Commerce Fulfillment Centre Worker (e.g., Amazon Warehouse), App-Based Food Delivery Courier (e.g., Deliveroo)
2: Online Freelancing (9 titles)	Online Freelance Video Editor, Online Freelance Graphic Designer, Online Freelance Tutor, Online Freelance Therapist, Online Freelance Writer, Online Freelance Musician, Online Freelance Personal Assistant, Digital Artist, Digital Journalist
3: Social Media (11 titles)	Beauty Blogger, Food Blogger, Online Video Content Creator (e.g., YouTuber), Social Media Fitness Influencer, Social Media Travel Influencer, Social Media Fashion Influencer, Online Content Moderator, Social Media Community Manager, Online Pornographic Content Creator (e.g., OnlyFans), Podcast Host, Professional E-Sports Player
4: Fintech (3 titles)	Cryptocurrency Trader (e.g., Bitcoin), Cryptocurrency Miner (e.g., Bitcoin), Online Stock Trader
5: Data Entry, Validation, and Trading (10 titles)	Artificial Intelligence Trainer, Chatbot Conversation Trainer, Software Tester, Video Game Tester, Online Microworker (e.g., Amazon Mechanical Turk), Data Entry Clerk, Digital Image Labeler, Data Miner, Online Data Collector, Data Broker
6: Digital Development and Design (13 titles)	Virtual Reality Architect, Video Game Designer, Website Designer, Machine Learning Programmer, Software Developer, User Interface (UI) Designer, Web Developer, Video Game Programmer, Mobile App Programmer, Hacker, Computer Scientist, Robotics Engineer, IT Systems Designer
7: IT Professionals (11 titles)	Chief Technology Officer (CTO), Data Protection Officer, Artificial Intelligence Consultant, Information Technology Consultant, IT Security Specialist, Technology Think Tank Analyst, Technology Policy Lobbyist, Data Protection Lawyer, Data Scientist, IT Manager, Internet Archivist
8: Digital Marketing and Sales (9 titles)	Digital Marketing Manager, E-Commerce Manager, Social Media Marketing Manager, Email Marketer, Search Engine Marketing Analyst, Technology Brand Ambassador, Spam Email Writer, Online Scammer, Chatbot Operator
9: Technology Entrepreneurship (5 titles)	Technology Start-up Founder, Technology Start-up Investor, Airbnb Host, E-Commerce Seller (e.g., Ebay), Online Drug Dealer

measurement. Our approach improves on previous attempts since extant measurements do not directly ask for OP, use ranking and sorting approaches rather than scoring, do not have fine-grained scales, or do not make use of the efficiency advantages of online surveys. Baran et al. (2016), for instance, only ask respondents to rank occupations between 1 and 5 on prestige, while the 2012 US General Social Survey (Smith and Son, 2014) asked respondents to rank occupations on a scale of 1–9 based on ‘social standing’. We developed, tested, and used a more scalable approach where occupational titles are scored on a 0–100 scale with a slider in an online survey (Gmyrek et al., 2024; Newlands & Lutz, 2024). We directly asked respondents, for the OP study, to answer *‘For each listed occupation below, please use the slider to indicate how you would rate the prestige of the occupation on a scale of 0 (the lowest level of prestige) to 100 (the highest level of prestige).’* Identical wording was used for the OSV study: *‘For each listed occupation below, please use the slider to indicate how you would rate the social value of the occupation on a scale of 0 (the lowest level of social value) to 100 (the highest level of social value).’*.

3.2.2. Measurement of independent variables

In addition to the OP or OSV assessments, we collected demographic and attitudinal variables to investigate the social stratification of the evaluations. For the demographic variables, we asked respondents for their age in exact years, gender (male, female, other), and education based on the latest version of the International Standard Classification of Education with 10 categories. In addition, we asked for household income and personal income (annually, before tax and compulsory deductions). British citizenship and whether the respondent was born in the UK where assessed with yes–no questions taken from the Office of National Statistics.

For the attitudinal variables, we had three questions from the World Value Survey that assess economic attitudes on a 1–7 scale based on their agreement to three statements: *‘There should be greater incentives for individual effort’*, *‘Government should take more responsibility to ensure that everyone is provided’* and *‘Hard work doesn’t generally bring success—it’s more a matter of luck and connections’*. In addition, we had one question, also from the World Value Survey, to assess political attitudes (*‘In political matters, people talk of “the left” and “the right”. How would you place your views on this scale, generally speaking?’*). Respondents could then place themselves on a 0–10 slider scale. Moreover, we measured life satisfaction and financial satisfaction, also based on the World Value Survey.

3.3. Sample

For the recruitment of participants across all phases of data collection, we rely on Prolific (Palan & Schitter, 2018; Peer et al., 2022). We collected in-depth OP and OSV assessments between 1 March and 26 March 2022, using Prolific’s representative sample option for the UK, where Prolific selects the respondents across age, sex, and ethnicity to mirror the population distribution. The reward for completing the study was £2.50, with a median response time of 19 min (SD = 15 min). This amounted to an hourly wage of more than £7.50.

OP and OSV were assessed in separate surveys as we did not want the same respondents to score occupations on these two dimensions concurrently to avoid priming effects and to maintain statistical independence. The digital economy occupations were evaluated as part of the larger study of all 580 occupation titles (Gmyrek et al., 2024; Newlands & Lutz, 2024). The surveys had to be launched sequentially with screening out for previous participation in any of the earlier data collections (including pre-tests). We carried out data quality checks and replaced a small number of erroneous responses due to unrealistically short response times or extreme straightlining individually with respondents of the same age group, gender and ethnicity. Our final sample size is 2429 respondents: 1219 respondents for OP and 1210 for OSV. 48.7 % of all respondents identify as male (1182 in total), 50.6 % as female, and the remaining 0.7 % have a non-male or non-female gender identification. The average age is 44 years (SD = 16). 77 % identify as White, 4 % as Mixed, 10.5 % as Asian, 6.5 % as Black, 0.5 % as Arab, and 1.5 % as Other. Education-wise, 5 % have lower secondary education as their highest degree; 27 % upper secondary school; 7 % a post-secondary non-tertiary education; 6 % a short-cycle tertiary education; 36 % a Bachelor; 17 % a Master degree; and 2 % a Doctorate.

3.4. Analysis

To assess the OP and OSV of the 76 digital economy occupation titles, we calculated different key indicators, compiling them in a master table (Appendix A). We use the arithmetic mean and standard deviation of each occupation title as the key indicators and are specifically interested in the intersection of OP and OSV. To analyse this intersection, we visualize the correlation via a scatterplot, highlighting outlier occupations and dividing the coordinate system into four quadrants based on the arithmetic mean across all 76 occupations. We used SPSS, Excel and Tableau for the data analysis and visualization. We also calculated the overall digital economy OP and OSV by averaging the OP and OSV of each respondent by the occupations they scored. These individual-level aggregate scores were used for a global regression analysis. In addition, we report how digital economy occupations compare to their non-digital economy counterparts (i.e., the most similar occupations outside of the digital economy in the same ISCO-08 unit group). Finally, we analysed how the occupations are structured in their social evaluation by regressing the individual level OP and OSV scores separately on demographic predictors. These 152 regressions are shown in Online Supplement B and C.

4. Results

Fig. 1 shows the 76 digital economy occupations on a scatterplot, where the location of an occupation within one of the four quadrants reflects its positioning in the socio-evaluative space. *Quadrant 1*: bottom left, (low OP, low OSV) contains stigmatized occupations (e.g., Online Drug Dealer, Hacker, Spam Email Writer) but also social media, cryptocurrency/fintech, operational sales (e.g., Chatbot Operator) and data-oriented clerical occupations (e.g., Digital Image Labeler, Online Microworker). *Quadrant 2:* top left (low OP, high OSV) has E-Commerce Fulfillment Centre Worker, Online Freelance Domestic Cleaner, Online Content Moderator, Online Freelance Therapist and Database Administrator. *Quadrant 3:* bottom right (high OP, low OSV) includes Data Broker, Online Freelance Writer, Online Freelance Musician, Online Freelance, Online Freelance Video Editor, Social Media Marketing Manager, Online Stock Trader, E-Commerce Manager, and Technology Brand Ambassador. With few exceptions, these occupations are either digital marketing and sales-oriented or online freelancing. *Quadrant 4:* top right (high OP, high OSV) includes the remaining occupations. It comprises IT professionals, software development and technology entrepreneurship.

Table 2 shows the regression results for the aggregated OP and OSV judgements.

Table 2
Regression of Occupational Prestige and Occupational Social Value Average across 76 Digital Economy Occupations on Predictors.

	Occupational Prestige	Occupational Social Value
Political Attitudes	0.06 (0.22)	0.61* (0.26)
Economic Attitudes 1	0.32 (0.34)	0.65 (0.44)
Economic Attitudes 2	1.22*** (0.33)	1.02* (0.42)
Economic Attitudes 3	−0.14 (0.27)	−0.66* (0.32)
Life Satisfaction	0.17 (0.30)	0.47 (0.30)
Financial Satisfaction	0.64* (0.27)	0.34 (0.27)
Age	0.01 (0.03)	−0.11*** (0.03)
Gender (Ref.: Male)	−0.61 (0.75)	0.53 (0.83)
Education	0.12 (0.21)	−0.30 (0.24)
Non-British Citizenship	2.94 (1.66)	3.11 (1.98)
Born Outside of the UK	3.12* (1.31)	1.57 (1.64)
Area of Residence	0.25 (0.35)	−0.86* (0.42)
Income	−0.09 (0.15)	−0.16 (0.17)
Ethnic Minority Status	1.73*** (0.38)	1.54*** (0.40)
Constant	23.54 (3.95)	28.93 (5.03)
R^2	0.08	0.09
N	1219	1209

Unstandardized regression coefficients; robust standard errors in brackets; *: $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

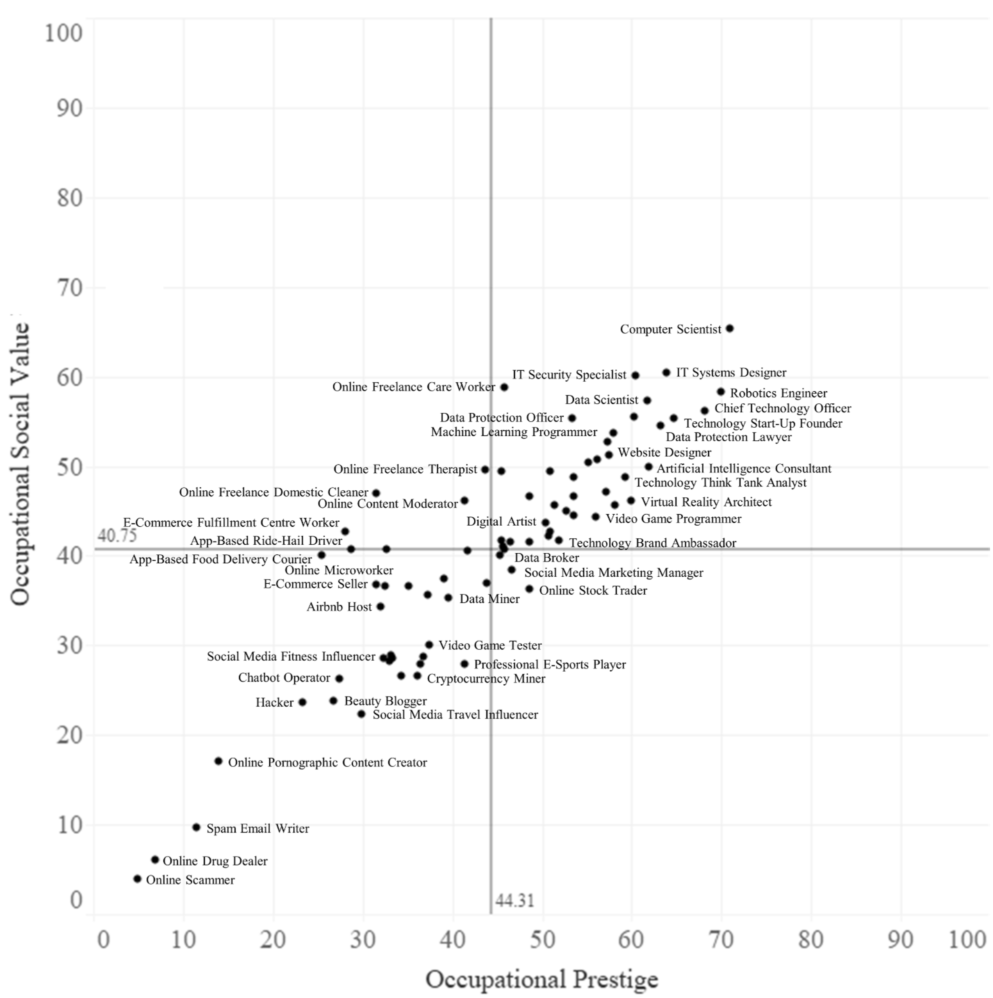

Fig. 1. Occupational Prestige-Occupational Social Value.

For OP, the significant predictors are economic attitudes, financial satisfaction, being born outside of the UK, and ethnic minority status. All are positive, indicating that individuals who want government to take more responsibility, who are more financially satisfied, who were born outside of the UK, and who belong to an ethnic minority group evaluate digital economy occupations as more prestigious. Ethnicity has the strongest effect. Those identifying as White see digital economy occupations as least prestigious (45), followed by individuals identifying as Mixed (49), Asian (50), Black (52), Arab (53), and Other (54). Eight percent in the variance is explained by the predictors. The OSV of digital economy occupations is significantly influenced by political attitudes, economic attitudes, age, area of residence, and ethnic minority status. The directionality of the coefficients implies that right-leaning individuals who want the government to take more responsibility, disagree that *'Hard work doesn't generally bring success – it's more a matter of luck and connections'*, live in urban areas, are younger, and have ethnic minority status see digital economy occupations as more socially valuable. In absolute terms, those in larger cities are more favourable towards digital economy occupations and their OSV (46), whereas those on the countryside are more critical (40) and those living in smaller cities (44) or in the suburbs (41) are in between.[4] White-identifying respondents have the most negative perceptions (41), followed those identifying as Mixed (45), Asian (47), Black (49), Other (49), and Arab (54). Nine percent in the variance is explained by the predictors.

4.1. Gig economy

Table 3 shows the information for the five *Gig Economy* occupations. Much heterogeneity is visible in both OP and OSV between these occupations.

Online Freelance Care Worker is clearly an outlier, with more than 20 OP points more than the lowest ranked occupation in this group (App-Based Food Delivery Courier) and almost 20 OSV points more. Strikingly, all occupations have remarkably large and negative OP-OSV differences (the largest across all digital economy occupations).

Comparing these occupations to their non-digital economy counterparts, a mixed picture emerges. E-Commerce Fulfillment Centre Worker has higher OP and OSV than Box Packer. Online Freelance Care Worker and Online Freelance Domestic Cleaner have higher OP than Homecare Aid and Domestic Cleaner. However, these occupations score lower in OSV. For App-Based Ride-Hail Driver, the comparative non-digital economy occupation is Taxi Driver and the latter has higher OP and OSV. Finally, App-Based Food Delivery Courier scores lower in both OP and OSV than Bicycle Courier.

Table 3
Aggregate Level Statistics for Gig Economy Occupations.

Occupation Title	Occupational Prestige (SD)	Occupational Social Value (SD)	Difference
Online Freelance Care Worker (e.g., Care.com)	45.89 (20.76)	58.80 (21.22)	−12.91
Online Freelance Domestic Cleaner (e.g., Helpling)	31.49 (19.90)	46.95 (23.09)	−15.46
App-Based Ride-Hail Driver (e.g., Uber)	28.73 (19.01)	40.73 (23.67)	−12.00
E-Commerce Fulfillment Centre Worker (e.g., Amazon Warehouse)	28.07 (19.22)	42.64 (24.28)	−14.57
App-Based Food Delivery Courier (e.g., Deliveroo)	25.45 (20.68)	40.10 (25.84)	−14.65

Regarding antecedents of OP perceptions, Online Freelance Care Worker is seen as significantly more prestigious among older adults. For App-Based Ride-Hail Driver, financial satisfaction, Non-British citizenship and ethnic minority status exert a positive influence. The OP of E-Commerce Fulfillment Centre Worker depends positively on right-leaning political attitudes and economic attitudes. Finally, economic attitudes, income (negative), and ethnic minority status (positive) matter for App-Based Food Delivery Courier. For OSV, the perception of Online Freelance Care Worker depends on economic attitudes, while ethnic minorities see App-Based Ride-Hail Driver more favourably. For Online Freelance Domestic Cleaner, economic attitudes, age, and ethnic minority status have a positive influence, while for App-Based Food Delivery Courier economic attitudes matter.

4.2. Online Freelancing

Table 4 shows the nine *Online Freelancing* occupations.

The group of online freelancers is relatively homogeneous when it comes to OP and OSV perceptions. While the OP of Online Freelance Graphic Designer sticks out, Online Freelance Therapist and Online Freelance Tutor have considerably higher OSV scores than the rest. These two occupations are also the only ones with a negative mean difference. Online Freelance Personal Assistant has both lower OP and OSV scores than the rest.

Online Freelance Tutor is in the same ISCO group as Secondary School Teacher. However, it has considerably lower OP and drastically lower OSV (49 vs. 73). Online Freelance Therapist has drastically lower OP and OSV (50 vs. 70) than Psychotherapist. The same picture, albeit less extreme, is visible for Online Freelance Writer. It has considerably lower OP than Novelist and Speech Writer and lower OSV than Novelist. However, the OSV difference to Speech Writer is much smaller. Online Freelance Musician scores much lower than Orchestra Musician in terms of OP (45 vs. 63) and markedly lower in OSV. By contrast, Street Musician scores considerably lower in OP than Online Freelance Musician but similarly in OSV. Personal Assistant has higher OP and OSV than Online Freelance Personal Assistant. Finally, Digital Journalist has much lower OP and lower OSV scores than Journalist (47 vs. 56).

The OP of Online Freelance Video Editor is positively affected by age and Non-British citizenship, with the same pattern for Online Freelance Graphic Designer. For Online Freelance Tutor, older age, more education, and ethnic minority status are positive predictors of OP. Finally, the OP of Digital Journalist increases with financial satisfaction, higher levels of education, countryside residence, and ethnic minority status. For OSV, political attitude is a significant predictor of Online Freelance

Table 4
Aggregate Level Statistics for Online Freelancing Occupations.

Occupation Title	Occupational Prestige (SD)	Occupational Social Value (SD)	Difference
Online Freelance Graphic Designer	52.63 (19.11)	44.93 (21.31)	7.70
Digital Artist	50.47 (18.69)	43.65 (21.38)	6.82
Digital Journalist	48.63 (19.88)	46.64 (21.64)	1.99
Online Freelance Video Editor	46.40 (18.78)	41.59 (21.36)	4.81
Online Freelance Writer	45.67 (19.60)	41.06 (21.02)	4.61
Online Freelance Tutor	45.50 (19.03)	49.38 (20.71)	−3.88
Online Freelance Musician	45.43 (20.81)	41.70 (21.68)	3.73
Online Freelance Therapist	43.64 (21.86)	49.53 (23.62)	−5.89
Online Freelance Personal Assistant	39.00 (18.52)	37.43 (21.49)	1.57

[4] 4 A one-way ANOVA supports this and the difference between these four groups is statistically significant at $p < 0.001$ ($F = 9.03$).

Graphic Designer, with right-leaning respondents evaluating the occupation as more valuable. Ethnic minority status is positively associated with OSV perceptions of Online Freelance Tutor.

4.3. Social Media

Table 5 shows the information for the 11 *Social Media Occupations* titles.

Since social media occupations such as YouTuber or Fashion Blogger are often seen as aspirational (Duffy, 2016; YouGov, 2021), it was surprising to see how low these occupations score in terms of OP and OSV. In fact, the OP scores of all seven occupations are below 40 and the OSV ones are all below 30. Online Video Content Creator fared best, while Online Pornographic Content Creator performed worst. However, the latter notably has a negative difference with higher OSV than OP. Comparing Food Blogger and Beauty Blogger, the former scores notably better, potentially indicating gendered and stereotyped perceptions. Among the three influencer occupations, Social Media Fashion Influencer is the most prestigious but Social Media Fitness Influencer is seen as most socially valuable, with Social Media Travel Influencer faring worst. This could have to do with the survey timing: travel influencers were negatively in the spotlight in the UK during Covid-19 lockdowns. Online Content Moderator has higher OSV than OP, whereas Social Media Community Manager has higher OP than SV. This reflects the content moderation literature, which shows how such work is straining and poorly paid but important for the maintenance of social media (Gillespie, 2020).

Food Blogger and Beauty Blogger score considerably worse than Journalist and Digital Journalist in both OP and OSV. Online Video Content Creator and Online Pornographic Content Creator are in the same unit group as Actor and Pornstar, with Online Video Content Creator accruing less OP and OSV than Actor but more than Pornstar. Social Media Community Manager is perceived as more prestigious but less socially valuable than Customer Contact Centre Clerk. Podcast Host scores lower in OP but marginally higher in OSV than Talk Show Host. Finally, Professional E-Sports Player is in a heterogenous unit group, together with Footballer and Professional Poker Player. It has substantially lower OP values than Footballer (41 vs. 59) and also lower OSV. However, it has higher OP and OSV scores than Professional Poker Player. For all these occupations, the standard deviations are high and so are the OP-OSV differences, showing heterogeneous evaluations.

The OP regressions indicate that for Online Content Moderator, older, Non-British individuals and ethnic minorities assign it more prestige. Income affects the OP of Social Media Community Manager negatively, while for Social Media Fashion Influencer, economic attitudes, financial satisfaction, being born outside of the UK and ethnic minority status come with higher OP evaluations. Finally, for Professional E-Sports Player, age and economic attitudes matter.

Turning to OSV, Social Media Community Manager is seen more favourably among women and its perception depends on economic attitudes. Social Media Fitness Influencers are seen as more socially valuable by urban residents, Social Media Travel Influencers by right-leaning people and those with stronger economic attitudes, and Social Media Fashion Influencers by younger individuals. Finally, for Professional E-Sports Player, age is very influential (unstandardized regression coefficient −0.46; Beta: −0.31). Thus, an 18-year-old evaluates Professional E-Sports Player as 29 points more valuable than an 80-year old. In addition to age, right-leaning political attitudes and being born in the UK come with higher OSV scores for this occupation.

Table 5
Aggregate Level Statistics for Social Media Occupations.

Occupation Title	Occupational Prestige (SD)	Occupational Social Value (SD)	Difference
Social Media Community Manager	45.79 (18.76)	40.66 (23.85)	5.13
Podcast Host	43.87 (22.27)	36.96 (23.69)	6.91
Professional E-Sports Player	41.44 (24.39)	27.94 (24.14)	13.49
Online Content Moderator	41.42 (19.71)	46.16 (21.73)	−4.74
Online Video Content Creator (e.g., *YouTuber)*	36.77 (25.98)	28.79 (25.89)	7.98
Social Media Fashion Influencer	34.25 (26.38)	26.58 (27.13)	7.67
Food Blogger	33.31 (21.06)	28.51 (23.26)	4.80
Social Media Fitness Influencer	33.05 (25.24)	28.24 (26.09)	4.81
Social Media Travel Influencer	29.91 (25.01)	22.36 (23.99)	7.55
Beauty Blogger	26.76 (20.42)	23.85 (24.50)	2.91
Online Pornographic Content Creator (e.g., *OnlyFans)*	13.91 (17.58)	17.13 (22.89)	−3.22

4.4. Fintech

Table 6 shows the information for the three *Fintech* occupations.

There is a schism between Online Stock Trader and the Cryptocurrency occupations, especially in terms of OP. All three occupations are characterized by high net positive differences between OP and OSV and thus seen as more prestigious than socially valuable, but on a low level.

Compared with Stockbrocker, Online Stock Trader has substantially lower OP and OSV. Cryptocurrency Trader is seen as much less prestigious (more than 20 points) and socially valuable than Stockbrocker. Cryptocurrency Miner, in turn, is less prestigious than its non-digital economy counterpart Miner. The latter has a negative OP-OSV difference of −9.53, which is the same difference as Cryptocurrency Miner but in the other direction (+9.53).

Only Cryptocurrency Miner is significantly influenced by any of the predictors: Those with lower income and ethnic minorities see it as more prestigious. Ethnic minorities, Non-British citizens and city dwellers see it as more socially valuable.

4.5. Data Entry, Validation and Trading

Table 7 shows the information for the ten *Data Entry, Validation and Trading* occupations.

Much heterogeneity exists in this group, mostly due to two occupations: Software Tester and AI Trainer. The high OP of these two occupations stands out. AI Trainer also has a very high OP-OSV difference of more than + 10. Videogame Tester is much worse ranked that Software Tester and the same is true for AI Trainer vs. Chatbot Conversation Trainer. Data Entry Clark stands out with a high negative difference of −8 and the difference for Online Microworker is also negative (-4). The data trading occupations have relatively low OP and OSV, with Data Broker scoring best. These three occupations are all have a positive OP-OSV difference.

Data Broker is the only occupation that has a non-digital economy counterpart. Compared with Stockbroker and Foreign Exchange Dealer, Data Broker has lower OP and OSV.

Table 6
Aggregate Level Statistics for Fintech Occupations.

Occupation Title	Occupational Prestige (SD)	Occupational Social Value (SD)	Difference
Online Stock Trader	48.59 (23.55)	36.29 (23.15)	12.30
Cryptocurrency Trader (e.g., Bitcoin)	36.44 (23.55)	27.92 (26.35)	8.52
Cryptocurrency Miner (e.g., Bitcoin)	36.08 (25.34)	26.55 (24.82)	9.53

Table 7
Aggregate Level Statistics for Data Entry and Validation Occupations.

Occupation Title	Occupational Prestige (SD)	Occupational Social Value (SD)	Difference
Artificial Intelligence Trainer	57.08 (19.97)	47.06 (23.56)	10.02
Software Tester	50.83 (18.42)	49.38 (21.26)	1.45
Data Broker	45.28 (19.91)	40.05 (21.19)	5.23
Data Miner	39.52 (22.28)	35.37 (23.92)	4.15
Videogame Tester	37.38 (21.23)	30.07 (21.39)	7.31
Online Data Collector	37.33 (19.54)	35.58 (21.62)	1.75
Digital Image Labeler	35.17 (20.71)	36.55 (22.70)	−1.38
Chatbot Conversation Trainer	33.18 (19.12)	28.89 (22.72)	4.29
Data Entry Clerk	32.60 (19.80)	40.67 (22.33)	−8.07
Online Microworker (e. g., Amazon Mechanical Turk)	32.52 (19.67)	36.58 (20.84)	−4.06

For OP, the regressions show how ethnic minority status is positive for Software Tester, Data Miner and Online Data Collector, and male gender for Videogame Tester. Economic attitudes affect the prestige perceptions of Data Entry Clerk, Online Microworker, Video Game Tester and Digital Image Labeller. The latter occupation is also significantly affected by area of residence, with city dwellers seeing it as more prestigious. Finally, Data Broker is positively affected by being born outside of the UK.

For OSV, men see Software Tester more favourably and women Chatbot Conversation Trainer. Ethnic minorities score Chatbot Conversation Trainer, Data Entry Clerk, Online Data Collector and Online Microworker as more socially valuable. City dwellers assess Videogame Tester, Data Miner, Data Broker and Digital Image Labeler more favourably. Young age, being born outside the UK (Beta 0.30), and non-British citizenship affect AI Trainer positively. Data Broker is negatively influenced by age and economic attitudes. Finally, the OSV scores of Digital Image Labeller are positively influenced by right-leaning political attitudes (same for Online Data Collector) and economic attitudes.

4.6. Digital Development and Design

Table 8 shows the information for the 13 occupation titles in *Digital Development and Design*.

This group has relatively high OP and OSV scores. Except for Hacker, all occupations have OP values greater than 50 and OSV scores close to 50. Computer Scientist is the occupation with both the highest OP and OSV, followed by Robotics Engineer in terms of OP and IT Systems Designer in terms of OSV. Except for Hacker, all occupations have higher OP than OSV scores. The difference is particularly big for Virtual Reality Architect (+14), Video Game Designer (+12) and Video Game Programmer (+12). Next to Hacker, Video Game Programmer is the occupation with the lowest OSV.

Contrasting the occupations with their non-digital economy counterparts, Virtual Reality Architect has substantially lower OP (60 vs. 75) and OSV (46 vs. 68) than Architect. Robotics Engineer is in the same group as Software Developer and User Interface (UI) Designer, both of which it exceeds in terms of OP and OSV. Compared with Computer Scientist, the two other digital economy occupations (IT Systems Designer, Machine Learning Programmer) in the same unit group have considerably lower OP and OSV.

The OP of Robotics Engineer rises with left-leaning political attitudes and economic attitudes, while the OP of Computer Scientist does so with economic attitudes and ethnic minority status. The OP of Virtual Reality Architect is significantly influenced by economic attitudes. For Website Designer, OP evaluations rise with left-leaning political attitudes, economic attitudes, and age. For Video Game Designer, ethnic minority status is the only significant predictor (positive), while the OP of Machine Learning Programmer is positively affected by left-leaning political attitudes and male gender. For Software Developer, financial satisfaction, being born outside of the UK and ethnic minority status are positive predictors, while for User Interface (UI) Designer ethnic minority status is positive and economic attitudes matter too. The OP of Web Developer depends on economic attitudes and being born outside of the UK (positive), while the OP of Mobile App Programmer is affected negatively by age. For Hacker, age and life satisfaction have a negative effect and ethnic minority status a positive one.

The OSV perceptions of Robotics Engineer are influenced by economic attitudes and those of Virtual Reality Architect vary positively with income. The perceived OSV of Video Game Designer is higher among younger people and men, also varying with economic attitudes. Financial satisfaction, male gender, and lower income lead to higher OSV scores of Machine Learning Programmer, whereas only age matters for Software Developer (negative). For User Interface (UI) Designer, male gender and ethnic minority status are associated with higher OSV. The OSV of Web Developer is negatively associated with age and income but positively with being born outside of the UK, and the OSV of Mobile App Programmer is influenced negatively by age, with additional economic attitudes effects. Strikingly, the age effect for Hacker is pronounced, with a B of −0.52 (Beta −0.32). Thus, an 18-year-old sees a Hacker as 32.5 points more socially valuable than an 80-year old.

Table 8
Aggregate Level Statistics for Digital Development and Design Occupations.

Occupation Title	Occupational Prestige (SD)	Occupational Social Value (SD)	Difference
Computer Scientist	70.99 (16.04)	65.35 (18.24)	5.64
Robotics Engineer	69.88 (16.11)	58.35 (21.68)	11.53
IT Systems Designer	63.89 (17.04)	60.41 (19.10)	3.48
Software Developer	60.27 (18.19)	55.55 (20.89)	4.72
Virtual Reality Architect	59.89 (19.27)	46.21 (24.12)	13.68
Video Game Designer	58.06 (19.69)	45.68 (23.81)	12.38
Machine Learning Programmer	58.00 (19.61)	53.68 (20.74)	4.32
Website Designer	57.48 (17.42)	51.31 (20.14)	6.17
Web Developer	56.14 (18.83)	50.71 (21.81)	5.43
Video Game Programmer	56.04 (20.24)	44.28 (22.41)	11.76
User Interface (UI) Designer	55.24 (17.26)	50.49 (21.27)	4.75
Mobile App Programmer	53.50 (18.87)	46.56 (22.01)	6.94
Hacker	23.28 (25.69)	23.71 (26.56)	−0.43

Table 9
Aggregate Level Statistics for IT Professionals Occupations.

Occupation Title	Occupational Prestige (SD)	Occupational Social Value (SD)	Difference
Chief Technology Officer (CTO)	68.10 (18.98)	56.10 (22.77)	12.00
Data Protection Lawyer	63.16 (19.61)	54.46 (23.30)	8.70
Artificial Intelligence Consultant	61.86 (19.77)	49.90 (23.63)	11.96
Data Scientist	61.70 (18.94)	57.24 (21.19)	4.46
IT Security Specialist	60.36 (18.97)	60.07 (20.40)	0.29
Technology Think Tank Analyst	59.22 (19.97)	48.73 (22.66)	10.49
IT Manager	57.35 (18.38)	52.79 (20.18)	4.56
Information Technology Consultant	53.55 (18.41)	48.73 (21.28)	4.82
Data Protection Officer	53.33 (19.90)	55.31 (22.74)	−1.98
Technology Policy Lobbyist	50.95 (19.31)	42.70 (23.98)	8.25
Internet Archivist	41.79 (19.44)	40.50 (22.53)	1.29

Group 7: IT Professionals

Table 9 shows the information for the 11 *IT Professionals* occupations. The scores, especially in terms of OP, are high. The lowest OP score (Technology Policy Lobbyist, 51) is still above the scale mid-point, but the OSV perceptions are lower. Data Protection Officer is the only occupation that has negative OP-OSV difference. The tendency is for relatively high net positive scores, especially for Chief Technology Officer (CTO), AI Consultant and Technology Think Tank Analyst, with a difference of more than + 10.

Data Protection Officer and CTO do not have non-digital economy equivalents. For IT Security Specialist, AI Consultant and IT Consultant, the most comparable occupation is Management Consultant. While all three of these occupations fare better in terms of OSV, IT Consultant has lower OP. Technology Think Tank Analyst and Technology Policy Lobbyist are in the same unit group as Political Adviser and Policy Analyst. Of these, Technology Think Tank Analyst scores best in both OP and OSV, whereas Technology Policy Lobbyist receives the lowest OSV judgements and the second lowest OP. Data Protection Lawyer fares considerably worse than Lawyer in both OP and OSV. Compared with Museum Curator, Internet Archivist has lower OP and OSV. Finally, Data Scientist has higher OP and OSV scores than Statistician.

Looking at the regressions and OP, for Data Protection Officer, economic attitudes, life satisfaction and being born outside of the UK all exert a positive influence, while for Chief Technology Officer, left-leaning political attitudes, male gender, countryside residence, income and ethnic minority status predict OP positively. The OP of Technology Think Analyst increases with age and ethnic minority status and that of Technology Policy Lobbyist decreases with age. The OP of Data Protection Lawyer varies with economic attitudes. For Internet Archivist, education and ethnic minority status affect OP positively, while for IT Manager, higher age, being born outside the UK and ethnic minority status significantly boost OP. The OP of Data Scientist is positively affected by economic attitudes and financial satisfaction.

For OSV, economic attitudes matter for Data Protection Officer, with younger and female respondents scoring the occupation more positively. Similarly, CTO is seen more positively among younger people. The OSV of AI Consultant is higher among younger citizens and those born outside of the UK, while income has a negative effect on the OSV of Technology Think Tank Analyst. For Technology Policy Lobbyist Analyst, economic attitudes matter, while younger and female respondents assess the occupation more favourably. The OSV of Data Protection Lawyer is negatively affected by age and education and positively by ethnic minority status, with economic attitudes mattering too. For Internet Archivist, age and income affect OSV negatively too, while for IT Manager right-leaning political attitudes, financial satisfaction, and ethnic minority status influence OSV positively. Finally, the OSV of Data Scientist is higher among young individuals, urban residents and ethnic minorities.

4.7. Digital Marketing and Sales

Table 10 shows the information for the nine *Digital Marketing and Sales* occupations.

High variance exists in the OP and OSV scores, especially between the more operational, sales-oriented occupations of Chatbot Operator, Email Marketer, Online Scammer and Spam Email Writer and the more managerial, strategic roles on the other. Digital Marketing Manager has the highest OP and OSV, while Online Scammer has the lowest. All occupations in this group fare better in OP than OSV and the difference is particularly large for the more managerial roles (e.g., Digital Marketing Manager). Social Media Marketing Manager, Digital Marketing Manager and E-Commerce Manager score in a similar range as Marketing Manager. Interestingly, Digital Marketing Manager has higher OP and OSV than Marketing Manager, whereas the other two occupations score worse, with Social Media Marketing Manager faring overall worst. Email Marketer has by far the lowest OP and OSV, while Search Engine Marketing Analyst fares better than Market Research Analyst. Online Scammer and Spam Email Writer were placed in the relatively large unit group 'Authors and Related Writers', scoring drastically worse than the other occupations here (Novelist, Speech Writer, Online Freelance Writer). Finally, Chatbot Operator shares its unit group with Call Centre Salesperson, having slightly higher OP but lower OSV.

Table 10
Aggregate Level Statistics for Digital Marketing and Sales Occupations.

Occupation Title	Occupational Prestige (SD)	Occupational Social Value (SD)	Difference
Digital Marketing Manager	53.51 (18.03)	44.45 (21.59)	9.06
Technology Brand Ambassador	51.87 (19.54)	41.74 (24.74)	10.13
Search Engine Marketing Analyst	50.66 (19.19)	42.24 (23.49)	8.42
E-Commerce Manager	48.69 (18.39)	41.60 (21.27)	7.09
Social Media Marketing Manager	46.56 (20.94)	38.47 (23.83)	8.09
Email Marketer	32.30 (18.62)	28.62 (22.37)	3.68
Chatbot Operator	27.47 (20.40)	26.24 (22.63)	1.23
Spam Email Writer	11.57 (17.89)	9.77 (16.04)	1.80
Online Scammer	4.96 (12.62)	3.94 (12.28)	1.02

Regarding OP perceptions, E-Commerce Manager is influenced significantly and positively by being born outside of the UK. For Search Engine Marketing Analyst, financial satisfaction, non-British citizenship and ethnic minority status all are associated with higher OP, with ethnic minority being positively associated with the OP of Chatbot Operator.

For OSV, both Social Media Marketing Manager and Digital Marketing Manager fare better among right-leaning people. For Social Media Marketing Manager, economic attitudes matter too, while for Digital Marketing Manager age does (same for E-Commerce Manager). Women, younger and less educated individuals see Email Marketer as more social valuable. For Search Engine Marketing Analyst, urban residence is positively associated with OSV. Finally, Chatbot Operator positively depends on ethnic minority status and urban residence.

4.8. Technology Entrepreneurship and Vendors

Table 11 shows the information for the five *Technology Entrepreneurship and Vendors* occupation titles.

OP and OSV are markedly low for the more vendor-oriented and platform-dependent occupations. Airbnb Host is the most prestigious occupation among these, but not by much and still on a low level. E-Commerce Seller is the occupation with the highest OSV, while Online Drug Dealer has extremely low OP and OSV. Both Airbnb Host and E-Commerce Seller have a higher OSV than OP score, whereas the opposite is true for Online Drug Dealer. Within the start-up occupations, Technology Start-Up Founder is seen as more prestigious and socially valuable than Technology Start-Up Investor. It also has the bigger OP-OSV difference.

Airbnb Host is in the same unit group as Bed and Breakfast Operator

Table 11
Aggregate Level Statistics for Vendor Occupations.

Occupation Title	Occupational Prestige (SD)	Occupational Social Value (SD)	Difference
Technology Start-up Founder	64.63 (19.77)	55.39 (20.76)	9.24
Technology Start-up Investor	51.45 (20.68)	45.62 (23.97)	5.83
Airbnb Host	32.04 (21.56)	34.40 (23.00)	−2.36
E-Commerce Seller (e.g., eBay)	31.53 (19.31)	36.71 (23.86)	−5.17
Online Drug Dealer	6.97 (16.16)	6.04 (14.60)	0.93

but has both lower OP and OSV. E-Commerce Seller is almost identical to Market Stall Vendor in terms of OP but has much lower OSV. Online Drug Dealer has similar, but slightly lower, OP and OSV scores than Street Drug Dealer. Technology Start-Up Founder scores lower in OP and OSV than CEO. However, the OP-OSV difference is much bigger for CEO, with a value of + 16. Technology Start-Up Investor scores considerably lower on OP but marginally higher on OSV than Investment Banker, indicating less of an OP-OSV differential.

Turning to the OP regressions, the only significant predictor for Airbnb Host is being born outside of the UK (positive), while economic attitudes matter for Online Drug Dealer. The OP of Technology Start-Up Founder rises with education and being born outside of the UK, while ethnic minority status has a positive effect for Start-Up Investor.

For OSV, younger people and ethnic minorities assess Airbnb Hosts more favourably, while age (negative), male gender (positive), and economic attitudes matter for Online Drug Dealer.

4.9. Aggregation and Synthesis

To show overall tendencies more clearly and highlight OP and OSV differences between occupational groups, rather than within occupational groups, we created an overview and summary table (Table 12).

The table groups and ranks the nine occupational groups from the highest aggregate evaluation (as the sum of averaged OP and OSV scores within an occupational group, except for four shadow economy outlier occupations) on the top left to the lowest aggregate evaluation on the bottom right. We grouped them into three levels: mid-high status, mid-status and low-status. The mid-high status occupational groups are labelled as Innovative Creators and Specialized Experts. They include Digital Development and Design, IT Professionals, and Online Freelancing occupations. Most Innovative Creators and Specialized Experts occupations have elevated skill levels and perform work that is either creative, developing or modifying software systems or creating digital artefacts, or managerial. The mid-status occupational groups are termed Strategic Implementers and Market Shapers, including Technology Entrepreneurship and Vendor, Digital Marketing and Sales, and Data Entry and Validation occupations (in this order). They are for most part characterized by a more operational scope and bring digital solutions to market, either through entrepreneurship (relying on existing infrastructure or creating new services), marketing or technology maintenance. The low-status occupations are labelled Essential Digital Service Providers, including Gig Economy, Fintech, and Social Media occupations. Interestingly, Gig Economy occupations scored higher than the (potentially) more aspirational and "hyped" Fintech and Social Media occupations, especially given their proportionally much higher OSV scores. The slightly higher OP scores of Social Media and Fintech occupations could not make up for this social value deficit. In terms of platform work, especially the difference between more white-collar and professional occupations (ranked number 3) in Online Freelancing and more blue-collar occupations of the Gig Economy is interesting (ranked number 7). These findings caution against subsuming heterogenous types of work, also in their social perceptions, into uniform labels such as the gig economy or digital labour.

Table 12
Overview and Synthesis of Digital Economy Occupational Groups, Ranked by Total Scores (Status).

Innovative Creators and Specialized Experts (Mid-high status)	1. Digital Development and Design (TS 112.33)	2. IT Professionals (TS 108.90)	3. Online Freelancing (TS 90.36)
Strategic Implementers and Market Shapers (Mid-low status)	4. Technology Entrepreneurship and Vendors (TS 87.94)	5. Digital Marketing and Sales (TS 82.06)	6. Data Entry and Validation (TS 78.11)
Essential Digital Service Providers (Low status)	7. Gig Economy (TS 77.77)	8. Fintech (TS 70.62)	9. Social Media (TS 64.33)

TS = Total Score (averages across each occupation in the occupational group for OP and OSV added up into a sum; dark/shadow economy occupations – Online Drug Dealer, Online Scammer, Spam Email Writer, and Hacker – not used in calculations).

5. Discussion and conclusion

5.1. General summary and discussion

In this article, we offered an in-depth analysis of the external societal evaluation of 76 digital economy occupations in the UK. The research contributes an external societal perspective on work evaluation to current research on workers' own internal perspectives and to research into the low quality of work in these sectors (e.g., Chen & Sun, 2020; Newlands, 2022b; Tubaro et al., 2020; Van Doorn, 2020). Overall, the OP of digital economy occupations is practically the same as that of non-digital economy occupations (45 vs. 46), but their OSV is considerably lower (42 vs. 50). In addition, occupations in the digital economy have higher levels of prestige than perceived social value. Only 15 out of 76 occupations (19.74 %) had higher OSV than OP. Thus, digital economy occupations suffer from a social value deficit not only internally, but also compared to 'regular' occupations. These contrasts suggest that a relational approach to the digital economy is valuable as it allows us to contextualize the topic. The finding of generally low scores in OSV also contributes to the on-going discourse around the expansion of jobs considered socially 'useless' (Graeber, 2018; Soffia et al., 2022). At the same time, the fact that more back-end roles fared the best supports the notion that the digital economy is heterogenous. Particularly low OP scores were assigned to occupations that are currently in the media spotlight, such as social media, fintech, gig economy, and customer-oriented sales occupations. The high media visibility of these occupations might not make them more prestigious but could rather have the contrary effect in that people might see them as more mundane, burdensome, and akin to basic service or otherwise low-skilled work.

5.2. Implications

Our article has *theoretical implications*. It contributes an external societal perspective on work evaluation to current research on digital economy workers' own internal perspectives (e.g., Chen & Sun, 2020; Newlands, 2022b; Tubaro et al., 2020; Van Doorn, 2020). By doing so, it adds to the burgeoning literature on the dynamics of social evaluation, a topic that has seen dynamic growth in recent years (Pollock et al., 2019). Specifically, our analyses connect to scholarship on occupational stigma and relational identities in new forms of work (Bucher et al., 2019; Easterbrook-Smith, 2023; Kamberidou, 2020; Newlands, 2021a, 2021b; Phung et al., 2021). Such research has demonstrated that, while workers in low-prestige jobs can feel pride and satisfaction, they can still struggle with the negative societal perceptions (Duemmler & Caprani, 2017), which can impact their self-esteem and sense of worth (Lamont, 2012; Petriglieri et al., 2019). It is thus not sufficient to limit research to only questions of political economy or labour processes, but one should also consider a more critical social perspective. The finding of generally low scores in OSV also contributes to the ongoing discourse around the expansion of jobs considered socially 'useless' (Graeber, 2018; Soffia et al., 2022; Walo, 2023). At the same time, the fact that more back-end roles, such as digital development and professional IT jobs fared the best supports the notion that the digital economy is heterogenous and that any approach to researching this sector should take a nuanced perspective.

Beyond the theoretical contributions, we also make *methodological advancements*, with implications for occupational research. Our digital economy occupation list, which is comprehensive and aligned with the most widely accepted occupational classification structure (ISCO-08), can be useful to fellow researchers. The secondary data we provide (i.e., the aggregate statistics on each occupation title) also allows others to investigate the digital economy more deeply both from a macro and micro perspective. From a macro perspective, the data can be triangulated with other occupational information, for example educational requirements, salary, or occupational composition (e.g., in terms of gender). From a micro and comparative perspective, our findings can be used for collecting primary data, for example for purposive sampling along particularly extreme occupations in terms of their average OP and OSV or OP-OSV difference.

Our findings also have practical implications especially for policymakers and managers. We found that ethnic minorities score digital economy occupations as more prestigious and more socially valuable than comparable non-digital economy occupations. Given that many ethnic minorities and migrants find employment in digital economy occupations, these findings might reflect a positive bias in self-selection into such occupations (Newlands, 2022b). However, the high percentage of ethnic minorities and migrants who find work in such occupations, particularly in lower-income sectors such as gig economy work, may be a factor in why such occupations have a low perceived prestige. Policymakers could elevate the OP of the least prestigious occupations, especially by making them more attractive to groups that scored them least favorably. A key avenue to do so is through improved working conditions and pay, as such measures would boost the attractiveness of these occupations and likely their prestige. Thus, regulation, for example regarding occupational safety standards and minimum wages, can play an important part in upgrading certain occupations. However, such regulation should be carefully tailored to the unique cultural and economic context of the UK, for example keeping in mind the importance of the service sector and the dynamism of its labor market. Elsewhere, such tailored policies might look somewhat differently. Tangible improvements in job quality might also be accompanied by image campaigns and outreach programs that are adapted to the unique cultural landscape of the UK to ensure their effectiveness. Similar outreach campaigns should be designed for occupations with low OSV (except for illegal and/or potentially harmful ones such as Online Scammer). The government could hire role models who show how the specific occupation has benefited society. For instance, for Virtual Reality Architect and Video Game Designer, positive examples of applications that improve mental health could be offered (e.g., benefitting youth with learning difficulties or serious games). For managers, our results highlight the need to be mindful of how the digital transformation affects occupational perceptions. We have shown how otherwise similar occupations (e.g., Journalist vs. Digital Journalist) can have diverging OP and OSV perceptions. Strongly established occupational norms and identities, especially in highly institutionalized professions (e.g., Lawyer), could make incumbents of these occupations see the intrusion of digital elements as a threat, especially within the UK's distinct professional environment. Managers concerned with the digital transformation of their organization should pay particular attention to evaluative dynamics over time and seek the dialogue with those affected.

5.3. Limitations and future research

Our research has limitations that may guide future research. Firstly, our data, while comprehensive, covers only one country. The UK has a specific occupational landscape that is different not only from non-Western countries but also from other European countries. Our findings might thus not generalize to other contexts. Future research should use our occupation list and investigate OP and OSV perceptions of the digital economy elsewhere. Secondly, we could not observe changes over time as our data is cross-sectional. Panel data would allow to identify the (in)stability of social evaluations over time and to also to disentangle within- and between-person effects. Thirdly, next to OP and OSV, other evaluative dimensions of occupations exist (e.g., social desirability of an occupation, perceived future-proofness, perceived environmental impact). We therefore encourage combinations of this data with other occupational variables. It would also be fruitful to combine the OP and OSV indicators with occupation-level data about other aspects of job quality such as working conditions and pay, constructing holistic indices of job quality of digital economy occupations. Finally, our analyses occurred on the occupation level rather than focusing on the internal heterogeneity of occupations. There is likely intra-occupational variety in OP and OSV along organizational (e.g., a software developer for Google accrues probably more OP than a software developer for a small start-up) and technological lines (e.g., type of software the software developer creates). Future research could evaluate such intra-occupational dynamics, especially with qualitative methods.

CRediT authorship contribution statement

Gemma Newlands: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Christoph Lutz:** Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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