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Social and facilitating influences in fintech user intention and the fintech gender gap

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A R T I C L E I N F O

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A B S T R A C T

Given the advances in technology, Fintech is an invaluable tool which allows unbanked people to access financial services when social, cultural, economic and technological factors affect their user intentions (UI). Despite the great importance of the role of social and facilitating influences in the adoption of Fintech services, little research has been conducted on how and what influences affect Fintech user intention (FUI) and whether there is a gender gap in FUI. Therefore, this study aims to help formulate effective Fintech policies and close the gender gap by investigating the role of social and facilitating influences and sociodemographic variables in FUI. The study sample comprised 237 participants, and the data were collected through interviews with the use of a structured questionnaire in Chattogram, Bangladesh. The collected data were analysed employing exploratory factor analysis and an ordered logistic regression model. The study also examined the Fintech gender gap by applying the Blinder Oaxaca decomposition model. The results reveal that image, compatibility and the experiences of Fintech use are the positive and significant predictors of FUI, with the perceived social norm for adopting Fintech being non-informative for users. There is a significant interaction between user compatibility and experience of use in relation to Fintech. Interestingly, perceived behavioural control negatively influenced females to adopt Fintech. Furthermore, the study found a gender gap in FUI. The findings have managerial implications.

1. Introduction

Financial technology (Fintech) is the application of technology to offer advanced financial services. It has quickly spread across the world and has unlocked great potential for economic growth and social welfare, like any other form of innovation. Fintech has become an impactful financial platform that facilitates financial inclusion [1] and sheds light on the drawbacks of the traditional banking system during the global financial crisis of 2008 [2]. As fintech services rapidly develop, characterised by their diverse nature and activities, Laidroo et al. [3] classified them into various dimensions, such as payments (i.e., mobile payment, mobile wallet); deposits

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and lending (i.e., crowdfunding, peer-to-peer lending); insurance (often coined as InsurTech); distributed ledger technology (e.g., blockchain enabled financial services); banking infrastructure (open banking); and investment management (e.g., technology enabled brokerage). Furthermore, Fintech includes financial planning, budgeting, virtual currencies, and cyber security [4]. This technology-driven financial innovation has had a material effect on financial markets and institutions [5]. Like that of financial institutions, the business model of fintech focuses on payment and loan services [6]. Therefore, to be competitive in the global market and achieve significant market potentiality, Fintech has appeared as a vital means for financial institutions, given the global scientific and technological trends [7,8]. Financial institutions have faced both opportunities and challenges, as Fintech facilitates financial services to unbanked people and disrupts traditional processes. However, when viewed from a gender lens, such financial services could be more widespread [9].

Globally, over one billion women still do not use or have access to the financial system, and more than 70 % of female-owned small and medium enterprises have inadequate or no financial services [10]. There is also a wide and ubiquitous gender gap in Fintech; 21 % of women use Fintech products, while the rate is 29 % for men [11]. Moreover, women living in rural areas have limited access to financial services, owing to the distance to bank locations, insufficient documents to open an account, and specific attitudes toward financial institutions. Although the gap is present in almost every country, when it comes to holding a bank account the gender gap is wider in Asian emerging markets such as Bangladesh, Pakistan and India [12]. The gap between men and women with bank accounts is 30 %, indicating a significant gender gap in financial services. However, given the financial inclusion opportunities offered by technology, Fintech can be a significant tool to reduce such a gap [9]. It promises to spur financial inclusion and is similar to closing the gender gap in accessing financial services. Therefore, policymakers need to understand the factors which influence the adoption of Fintech in order to reduce the gender gap underlying Fintech services.

Under the three mechanisms of compliance, internalisation and identification, social influence affects individuals' technology adoption [13]. Internalisation and identification lead individuals to be influenced by the gaining of social status [13]. Image, which represents social influence in the innovation diffusion theory, is defined as the level to which the application of an innovation is perceived to enhance one's social status, and such status was found to positively influence individual technology adoption [14]. Research has revealed that Fintech has been able to reduce the gender gap by giving more access to financial inclusion and reducing income inequality [15,16]. Furthermore, facilitating factors and conditions affect technology adoption behaviour significantly [17,18]. Compatibility is one of the vital contextual factors in diffusion of innovation theory, which applies the prediction of technology adopters' behaviours and identifying factors that require additional facilities or effort for successful system implementation [19]. Despite their great importance, little research has been conducted on how social and facilitating factors affect the user intention (UI) of Fintech. Furthermore, no evidence has been found that supports analysis of the role of social and facilitating influences on the Fintech gender gap. These research gaps are even wider in emerging and developing economies. Therefore, this study aims to fill these knowledge gaps.

Overall, in addressing these gaps, the objective of the study is to specifically examine the gender gap by analysing the role of social and facilitating influences in Fintech user intention (FUI), thus helping policymakers to formulate appropriate Fintech policy. Therefore, the general research question is: how do we investigate the gender gap while analysing the role of social and facilitating influences on FUI? To answer the question, the study uses a questionnaire design to elicit information on personal views and choices made concerning the UI of Fintech by gender. Exploratory factor analysis and a logistic regression model are used to explore the link between social and facilitating influences and UI. The study also employs the Blinder Oaxaca decomposition model to examine the Fintech gender gap. Therefore, to address any divergence in the findings and gain full insight into the research objective, the facilitating condition, perceived behavioural control, and compatibility were considered to construct the facilitating influence factor. Second, image, social norms and social factors are incorporated to comprehensively examine the impact of social influence on FUI. We thus expect the study findings to provide a new research framework that will allow Fintech companies to flourish in the field by obtaining an increased market share and contributing to the leverage of the Fintech sector, creating new financial policies and developing the digitalisation of services in the economy.

The paper is organised as follows. Section 2 contains the theoretical framework, followed by the conceptual model. The data and methods are then described in section 3, while section 4 considers the results and analysis. The discussion is presented in section 5, and the paper ends with section 6, namely the conclusion and implications.

2. Theoretical framework

Over the years, multiple theories have been developed addressing the adoption of new technology. As stated in the unified theory of acceptance and use of technology (UTAUT), significant factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions affect the UI to adopt technology [13]. Later, these factors, with the inclusion of social impact, were validated by UTAUT2, an extension of UTAUT, and shown to have an influence on consumers' behavioural intention to accept and use technology [20]. In addition, TAM2, an extension of the technology acceptance model (TAM), incorporates social influence processes that significantly influence user acceptance of technology [21]. By applying these theories, together with the advantages of technological innovation, financial services have become more accessible to people by reducing the barriers associated with the traditional modes of such services. Furthermore, the dependence on technology and the adoption of digital financial services sharply increased during the Covid-19 pandemic, with access to Fintech, which has brought households, individuals and unbanked rural people into the financial system, contributing to financial inclusion [22,23].

The literature reveals that social influence and perceived usefulness affect Fintech adoption [24,25]. Conversely, Antwi-Boampong et al. [26] found that social factors did not influence the behavioural intention of the port users to enrol in Fintech. In addition, social factors have been shown to have no impact on the intention and use of mobile money services [27]. Conforming to the theory of planned behaviour (TPB), consumers' behavioural intention is influenced by subjective norms, perceived behavioural control (PBC), knowledge, and experience [28]. The social influence process comprises three interrelated factors: subjective norms, image and voluntaries [21]. A subjective norm, which is defined as the perception a person holds of what is important to them, has also been found to be a direct determinant of behavioural intention in the theory of reasoned action (TRA) [29]. Consistent with the findings of the theory, social norms significantly influence the UI to adopt mobile finance services (MFS) [30].

The use of innovation is believed to enhance the status of individuals in society; known as an image, it is found to be one of the eight other factors that impact the use of new technology [14]. Studies regarding the impact of brand image on Fintech services show that it positively affects user perceptions of satisfaction and attitude toward using Fintech services [8,31]. Likewise, enterprise image positively affects the intention to use Fintech services [32]. Therefore, we expect a positive relationship between social influence, facilitating conditions and hedonic motivation [33]. In addition, Ouattara [34] found that the facilitating condition predicts UI and influences customers' intention to purchase using mobile commerce [35]. Accordingly, if users perceive that all facilities or support are available to use the technology, they will be positively motivated to adopt it. Technology-driven services have been increasing and disrupting traditional business moods, particularly during the Covid-19 pandemic; business organisations are trying to reach customers and provide services to them through technology. In the case of financial technology adoption, if consumers perceive that appropriate guidance and the required support are available, then they will be motivated to adopt Fintech services. Conversely, Antwi-Boampong et al. [26] found no impact of facilitating factors on UI, indicating mixed findings on the impact of promoting conditions on FUI. As behaviour can be predicted with known behavioural control, future studies could develop the analysis of the impact of facilitating conditions on FUI.

An individual's behaviour is influenced by PBC, which is defined as the perception of the ease or difficulty of an individual to display the behaviour of interest [28]. To satisfy customers or understand their demand and choices, discerning customers' behaviour plays a significant role in whether customers will accept services or not. When an innovation is considered consistent with the existing needs, values and experience of potential it is referred to as compatibility, influencing the adoption of new technology [14]. That is, when users find the technology to be relevant to or addresses their needs, they will accept it. Consistent with the relevant theories, several studies have established behavioural intention as an outcome variable in examining the relationship between behavioural intention and social and facilitating factors [24,26,36]. Furthermore, according to the UTAUT2 model, sociodemographic variables such as age, income and experience have been hypothesised to moderate the effect of fintech on behavioural intention [20]. Mahmud et al. [37] found that the Fintech adoption rate was higher among the young and males, meaning that the number of females accessing fintech services was lower than that of males, thus indicating a gender gap.

To examine the gender gap in the adoption of Fintech services, the Blinder-Oaxaca decomposition model was used. With the advantages of technological innovation, financial services have become more accessible to people following the reduction in the barriers associated with the traditional modes of financial services. Against this backdrop, Fintech encompasses internet banking, card banking, mobile banking and financial services through digital media [38], which is crucial in creating more space for people to benefit from financial services, regardless of gender. For example, women's access to financial institutions was previously hindered by factors such as insufficient documents for opening a bank account, distance, and socioeconomic and cultural factors [39]. Now however, Fintech helps women to be financially empowered by eliminating some of these obstacles [12]. The dependence on technology and the adoption of digital financial services sharply increased during the Covid-19 pandemic, and access to Fintech, with households, individuals and the unbanked rural people brought into the financial system, has contributed to financial inclusion [22,23]. Although Fintech reduces the gender gap in such inclusion [15], the disparities in digital finance services remain significant across regions and countries [40].

Therefore, we expect that widespread women's access to Fintech services will reduce the gender gap in financial inclusion. The study focuses on the role of social and facilitating influences, together with sociodemographics, on households' intention to use Fintech, as depicted in the conceptual framework (see Fig. 1).

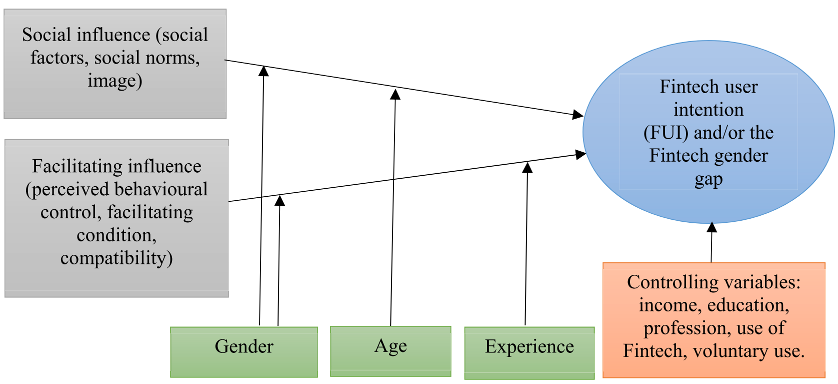

Fig. 1. Conceptual model.

3. Data and methods

3.1. Sample and data collection

Despite the advances made, the financial inclusion gender gap remains wide in Bangladesh, with as many as 65 % of women being unbanked [12,41]. Therefore, mobile financial services (MFS) have become very popular, with 57.35 million active account users [42], although the gender gap in owning the mobile phone that is required to enjoy MFS is almost 30 % [41]. Considering the above information, it can be inferred that a significant number of people are benefitting from Fintech services, although many women remain not included, indicating a high potentiality for new Fintech users. To answer the research question, a survey was conducted in Chattogram, the commercial capital city in Bangladesh. People living in this city are relatively wealthier than the rest of the country [43] and were therefore suitable participants for our exploration of the growing awareness of Fintech in the emerging economy of Bangladesh [44]. It took almost three months to collect the research data, starting on December 3, 2022, and ending on March 7, 2023. With consideration of the budget limitations, 260 respondents were randomly selected to complete the questionnaire. Of the 260 observations, 237 were finally employed as the study sample, as 23 questionnaires contained incomplete information.

Furthermore, a pre-survey was conducted on 35 respondents before proceeding to the main survey in order to determine if they understood what they were being asked in the questionnaire or if there was any ambiguity in the questions. As this demonstrated that the respondents understood the questionnaire, the survey was undertaken. The Ethical Review Board of the University of Chittagong approved the ethical standard of the survey content. The purpose of the study was specified to the participants, and participation consent was clarified in a motivational letter, together with the relevant textual information about Fintech (Appendix 1). To ensure convenience for the respondents, they were interviewed with structured questionnaires which were written in their first language, Bengali. Each interview took 20 min on average. The statistical and econometric tools employed for the study included descriptive statistics, an order logistic regression model, and the Blinder-Oaxaca (BO) decomposition model.

3.2. Questionnaire and measures

The questionnaire was split into two sections. Section A comprised three constructs: the social and facilitating influences, and user intention. The section was further divided into seven parts to measure the social and facilitating influences of Fintech adoption. From part 1 to part 3, social factors, image and social norms represented the social influence construct. The facilitating influence was represented by PBC, the facilitating condition, and compatibility in part 3, part 4 and part 5, respectively. Part 6 represented the FUI. Each part contained questions in the form of statements from previous studies. The respondents gave their opinion on the statements choosing a response based on a seven-point Likert scale. 1 showed they strongly disagreed with the statement, while 7 indicated they strongly agreed with it; 4 represented that they neither agreed nor disagreed with the statement.

To measure social influence, four statements were presented to the respondents [45]. For instance, they were asked to what extent they agreed with the statement, "I use the system because of the proportion of coworkers who use the system". Under the image scale that was constructed with the prestige issue from Fintech usage, three statements were designed [14]; for example, participants were asked to indicate the extent to which they agreed with the statement "People in my organisation who use Fintech have more prestige than those who do not". Respondents were given six statements to measure social norms, constructed based on the perception of consumers about the most important persons for them in relation to Fintech usage [45,46]. For instance, respondents were asked to what extent they agreed with the statement: "Most people who are important to me approve of my frequently using Fintech". PBC was measured by five statements considering the control of consumers over the Fintech system, the availability of resources for using Fintech, and the compatibility of Fintech with other technology [28,47]. For example, the degree to which respondents agreed with statements such as "I have control over using the system" was examined. The facilitating condition was represented by three statements taken from previous research [45], which addressed the guidance and assistance available to consumers when using Fintech. For example, the participants were presented with the statement "A specific person (or group) is available for assistance with Fintech", and were asked to indicate the degree to which they agreed with it. With setting the three statements, the compatibility scale was measured

Table 1
Exploratory factor analysis outcome of social factors.

Sl. Nr.	Observed Variables	Factor Loadings	
		Social Factor	Image
1.	My supervisor in my workplace is very supportive of the use of the fintech system.	0.786	
2.	I use the fintech system because of the proportion of colleagues who use the system.	0.644	
3.	The opinion leader of this society has been helpful in the use of the fintech system.	0.626	
4.	People in my area who use the fintech system have a high profile.		0.950
5.	Having the fintech system is a status symbol in my society.		0.880
6.	People in my locality who use Fintech have more prestige than those who do not.		0.783
	KMO score	0.704	
	Bartlett's test of sphericity: approximate Chi-square (χ^2)	432.342 ($p < 0.000$)	
	Degrees of freedom (*d.f.*)	15	
	Total variance explained (%)	64.02	
	Cronbach's Alpha (α) ($n = 6$)	0.737	

based on the compatibility between the system and work style [14]. For example, the respondents were asked the extent to which they agreed or disagreed with the statement “Using the system is compatible with all aspects of my work”. Finally, the UI construct was represented by five statements that reflected consumer intention to adopt Fintech [48]. For instance, the respondents were asked to show how far they agreed with the statement “I intend to use Fintech in the next month”.

Section B of the questionnaire covered the demographic characteristics of the respondents, encompassing age, gender, income, education, experience of Fintech, income, occupation, Fintech usage, and membership of any social organisation. They were assured that the information they shared regarding their personal characteristics would not be revealed and would be kept secret. The study employed exploratory factor analysis (EFA) to decide the best number of dimensions and their common connotations based on the responses to the specific constructs and to build a pattern matrix (Tables 1 and 2). The mean values of the three observations for ‘social factors’ and ‘image’ were then measured for use as independent variables. Similarly, facilitating influences were assessed and employed in the models.

3.3. Econometric modeling

3.3.1. Ordered logistic regression model

The study developed an empirical model to test if consumers’ perceived social and facilitating factors affected FUI. A quantitative scale can reflect meaningful qualitative differences; therefore, sorting such categorical indicators makes it easier to make subjective judgments about the value of different scales. On the seven-point Likert scale of strongly agree (7) to strongly disagree (1), the mean value of reliable and valid measurements was used to categorise the respondents’ perceived value of FUI. This value was classified into three levels: low (1), medium (2) and high (3), indicating multiple dependent variables [49].

$$\text{Y} * (\text{User Intent}) \begin{cases} Y = 1, \textit{if mean scale scores} \leq 4.00 \\ Y = 2, \textit{if } 4.10 < \textit{mean scale scores} < 5.99 \\ Y = 3, \textit{if mean scale scores} \geq 6.00 \end{cases}$$

The response variable calculated above was regressed on the social and facilitating influences and a set of socioeconomic variables to determine the factors affecting perceived FUI. Since the response variables of main interest, factors that determine consumers’ value of FUI (three levels), had an ordinal categorical nature, an ordered probit model was employed to analyse such polychotomous response data. The latent continuous variable, y^*, is a linear assortment of certain estimators, x, with an error term that is normally distributed:

$$y_i^* = x_i^{'}\beta + \varepsilon_i \ldots, \quad (1)$$

where y^* is the dependent variable that indexes consumers’ perceived FUI level; x is a vector of social and facilitating influence and socio-demographics parameters to be estimated β; and ε is the error term. The responses of these categories are thus observed in equation (2) when the underlying continuous response falls in these three intervals as:

$$\begin{aligned} y &= 1 \textit{ if } y^* < \mu_1 \\ &= 2 \textit{ if } \mu_1 < y^* < \mu_2 \\ &= 3 \textit{ if } y^* > \mu_2 \ldots, \end{aligned} \quad (2)$$

The μ's are unknown threshold parameters to be estimated with β. These parameters determine the estimations for the different observed values of y^* and can be interpreted as intercepts in equation (1). In the ordered logit (Ologit) model, the intention is to estimate consumers’ FUI. Positive parameters indicate that the predictor variable is likely to increase the probability of intent to use Fintech. Alternatively, negative parameters show that the explanatory value tends to decrease the FUI probability. The Ologit analysis

Table 2

Exploratory factor analysis outcome of facilitating factors (FC = facilitating condition, Com. = compatibility, PBC = perceived behavioural control).

Sl. Nr.	Observed Variables	Factor Loadings		
		FC	Com.	PBC
1.	A specific person (or group) is available for assistance with Fintech.	0.842		
2.	Specialized instruction concerning Fintech was available to me.	0.836		
3.	Guidance was available to me in the selection of the Fintech system.	0.745		
4.	Using the Fintech system is compatible with all aspects of my work.		0.850	
5.	I think that using the Fintech system fits well with the way I like to work.		0.849	
6.	Using the Fintech system fits into my work style.		0.758	
7.	I have the necessary resources to use Fintech.			−0.844
8.	I have control over using the Fintech system.			−0.791
9.	I have the knowledge necessary to use Fintech.			−0.732
	KMO score	0.747		
	Bartlett’s test of sphericity: approximate Chi-square (χ^2)	743.752 ($p < 0.000$)		
	Degrees of freedom (*d.f.*)	36		
	Total variance explained (%)	68.89		
	Cronbach’s Alpha (α) ($n = 9$)	0.796		

then tests the model fit by examining the fit indexes and criteria. The model's log-likelihood = −141.1156, and the pseudo R^2 = 0.4406. In addition, the probability of the model likelihood ratio χ^2 (24) = 222.33 was 0.000, which is lower than the recommended level of significance of 0.010 ($p < 0.01$). Consequently, it was established that the model fitted the data.

3.3.2. Linear BO (Blinder Oaxaca) decomposition model

To understand every aspect of inequality, a multiple regression model can be used to decompose inequality into its components. Blinder [50] and Oaxaca [51] proposed a method to examine the factors associated with racial or gender wage inequality and discrimination in the labour market. The Blinder-Oaxaca decomposition model is applied when measuring the outcome difference in means between two groups [52]. For instance, Wagstaff et al. [53] applied the model to examine health inequality on the basis of poverty status, while Etezady et al. [54] used the same model to study the generational differences in transportation-related attitudes. The method has also been applied to explain inequalities in the health outcomes of two groups [55]; accordingly, it can be applied to examine inequalities in the Fintech adoption of two groups. As the linear BO decomposition method deals with the continuous outcome variable [56], the outcome variable of the study is FUI, which was measured on the Likert scale, and is also the continuous variable employed in the linear BO decomposition method. This rationale centres on the fact that Likert variables with five or more categories can often be used as continuously [57]. The alternative method is more common; the mean of two or more Likert or ordinal variables is taken to create an approximately continuous variable. Etezady et al. [54] used threefold BO decomposition to capture the Generational difference, citing that it provided a more consistent interpretation of differences. Furthermore, the twofold decomposition method does not separate the interaction effect from the endowment effect and the co-efficient, although it does provide more straightforward interpretation. Therefore, this study applied both threefold and the twofold decomposition in examining the gender gap in the UI of Fintech.

3.3.2.1. Threefold decomposition approach. The approach started with the formulation of a linear regression model with y as the dependent variable for the two groups: group 1 and group 2, as demonstrated in Equation (3). Males were denoted by group 1, and female by group 2.

$$Y_1 = X_1^{'}\beta_1 + \epsilon_1 \quad \text{and} \quad Y_2 = X_2^{'}\beta_2 + \epsilon_2 \ldots, \tag{3}$$

Since the expected error term (ϵ_e) was assumed to be zero, the differences in the mean value of the outcome variables between the two groups can be expressed as:

$$(Y_2) = \mathrm{E}\,(X_1)^{'}\,\beta_1 - \mathrm{E}\,(X_2)^{'}\,\beta_2 \,\ldots, \tag{4}$$

The gap in mean outcome (ΔE(Y)) can be attributed to three components, written as follows:

$$\Delta\mathrm{E}(\mathrm{Y}) = \underbrace{\{E(X_1) - E(X_2)\}^{'}\beta_2}_{endowments\ effect} + \underbrace{E(X_2)^{'}(\beta_1 - \beta_2)}_{coefficients\ effect} + \underbrace{\{E(X_1) - E(X_2)\}^{'}(\beta_1 - \beta_2)}_{interaction\ effect} \tag{5}$$

Equation (5), which shows the decomposition, is written from the viewpoint of group 2 (the female group). In this study, the endowment effect shows the expected change in the behavioural intention of females (group 2) if they had group 1 (male) predictors. Likewise, the coefficient effect measures the expected change in the mean of group 2, if it had a coefficient of group 1. Finally, the interaction term shows the endowment and coefficient effects simultaneously.

3.3.2.2. Twofold decomposition. The twofold decomposition approach, like the threefold one, began with estimation of the linear regression models, shown in Equation (1), for the two groups, while calculating the mean value differences between males and females, as shown in Equation (4). In the case of a twofold approach, the mean differences between two groups can be split into two parts, as shown in equation (6).

$$\Delta\overline{Y} = \underbrace{(\overline{X_1} - \overline{X_2})^{'}\beta_2}_{explained\ component} + \underbrace{\overline{X_1}^{'}(\beta_1 - \beta_2)}_{unexplained\ component} \tag{6}$$

Twofold decomposition captures the differences in the mean between two groups into two components: explained and unexplained parts. The first part in equation (6) captures the differences, which can be attributed to the characteristics or endowment, while the second term captures the differences which cannot be explained, which is hence considered as the discrimination effect. The first part of the twofold decomposition, identical to that of the threefold approach, represents the differences in the means deriving from the quantity effect or explained components, which is weighted by the vector of the coefficients of group 2 (the female group), whereas the second part captures the unexplained or discrimination components, also containing unobserved variables, which is weighted by the vector of the mean explanatory variables in group 1 (the male group).

3.3.2.3. Detailed decomposition. Since total decomposition does not indicate the contribution of each predictor to the mean value differences between the two groups, detailed decomposition is deployed in equation (7) to investigate the single predictor contribution toward the explained differences (the endowment effect) and the unexplained differences (the discrimination effect). For instance, detailed decomposition would answer the question of which predictor variables contribute to the gender gap in FUI. The equation of the detailed decomposition is as follows:

$$\Delta \widehat{Y} = \underbrace{(\overline{X_1} - \overline{X_2})^{'\widehat{\beta}_1}}_{contribuitons\ to\ explained\ part} + \underbrace{\overline{X_2}^{'}(\widehat{\beta_1} - \widehat{\beta_2})}_{contributions\ to\ unexplained\ component} \ldots, \tag{7}$$

The contributions of the single predictors to the explained part are the sum of the single contributions [52], where $\overline{X}$, referring to the single regressor $\widehat{\beta}$, is the associated coefficients. The contribution to the explained part represents the single predictors' contribution to the differences in this part, while the contributions to the unexplained part represent the individual predictors' contribution to differences in this part.

4. Results

4.1. Descriptive statistics of respondent demographics and socioeconomic variables

The demographic profile of the respondents is shown in Table 3, where it can be seen that the respondents who participated in the survey were 61.6 % male and 38.4 % female, with an average age of 36.88. Their average income per month in Bangladeshi taka (BDT) was 42,736.29, with their average of 15.81 years of education possibly reflecting that they were sufficiently educated to use Fintech. Among the respondents, 67.9 % were employees, while 28.3 % and 3.8 % were self-employed and retired, respectively. The mean value of Fintech experience was 3.23 years, indicating that Fintech services have expanded in recent years. The survey data also show that 75.5 % of respondents used Fintech, with 68.4 % using it voluntarily, and 7.2 % mandatorily. 48.9 % and 18.6 % of the respondents chose international authority and national authority respectively, in relation to the provision of accurate technology quality inspection certificates, which sheds light on the mistrust of authorities inside the country.

4.2. Social and facilitating influences affecting fintech adoption

The study first estimated the effect of the social and facilitating influences, together with the sociodemographic variables, on FUI, using the ordered logit model shown in Table 4. The results show that image positively affects FUI, which is consistent with the

Table 3
Descriptive statistics of the demographic profile of the respondents.

Variable	Mean, S.D.
Age (Mean ± St. Dev.)	36.88 ± 9.55
Gender (%)	
Female	38.4
Male	61.6
Income per month (Mean ± St. Dev.)	42736.29 ± 19845.46
Education (in years)	15.81 ± 3.28
Occupation (%)	
Other	3.8
Employee	67.9
Self-employed	28.3
Experience of using Fintech in years (Mean ± St. Dev.)	3.23 ± 2.907
Fintech user (%)	
No	24.50
Yes	75.50
Type of use (%)	
Voluntary	68.4
Mandatory	7.2
Not applicable	24.5
Membership of social club (%)	
No	62.4
Yes	37.6
Trust in authority (%)	
Local authority	4.2
Private authority	8.4
National authority	18.6
International authority	48.9
All equally	15.6
Not any at all	4.3
N = 237	

USD 1 = BDT 105.

literature [8,31]. PBC and compatibility also show a positive and statistically significant relationship with FUI, also consistent with previous finding [58]. Although the facilitating factor was found to be positively related to FUI, it was statistically non-significant. Among the sociodemographic variables, other professions (apart from employee and self-employed) and the 'Fintech user' (those using Fintech) variables reveal a statistically significant positive impact on FUI. Other variables, such as age, gender (female), income, education, occupation, experience of using Fintech, and voluntary/mandatory use of Fintech were found to be statistically insignificant. The moderating or interactive effect was also examined to optimise the FUI process, if there was one, among the components in the study.

The interaction between image and female shows a positively significant impact, meaning that females use Fintech to leverage their status in the workplace and society. In addition, gender (female) moderates the effect of image on FUI. Their technological knowledge and the availability of resources motivated females to use Fintech [59]. Moreover, image and age together revealed a significant negative relationship, indicating a moderate relationship between image and FUI. On the other hand, PBC and females showed a significant negative relationship with Fintech adoption, contrary to previous research [60]. Likewise, the interaction effect of the compatibility and experience of using Fintech showed a positive and significant effect on FUI. Such findings indicate that experienced users can fit the Fintech system well into their way of work.

4.3. Gender gap analysis of the adoption of fintech

The linear regression model for group 1 (males) and group 2 (females) was estimated separately, incorporating the social and facilitating factors and sociodemographic variables. The regression model for group 1, which is the reference group in the study, and the regression model for group 2 (the non-reference group) are shown in Appendix 2. The explanatory variables, such as social factors, PBC, facilitating condition, compatibility, experience of using Fintech, use of Fintech, and club membership, were to be found to significantly influence females' FUI. On the other hand, image, facilitating condition, compatibility, profession, experience, and trust in providing accurate technology quality inspection certificates affected males' FUI. The facilitating condition, compatibility and experience were common factors influencing both male and female consumers' FUI. The decompositions were then calculated based on the outcomes of the regression models. The twofold decomposition showed that 52.04 % of the gender gap difference in user intention was from endowment effects. In contrast, 47.96 % of the gap remained unexplained. The unexplained part is termed as discrimination, showing a gender gap in FUI, although the unexplained part may also be contributed to by unobserved variables which were not included in the study [52].

Table 5 summarises both the threefold and the twofold decomposition results. The mean value for the behavioural intention to adopt Fintech is 2.3956 for males and 2.0958 for females, indicating a 0.2997 difference that is statistically highly significant in both approaches. The threefold approach splits the decompositions into three components, demonstrating the differences in behavioural intention between males and females. The gap or difference is contributed to by endowments at 54.95 % (0.1647/0.2997), coefficients at 86.78 % (0.2601/0.2997), and interaction at −41.78 % (−0.1252/.2997). If the females had the same characteristics or endowments as the males, this could have reduced the gap in user intention to use Fintech by 54.95 %. The coefficient portion of the gap

Table 4
Ordered logit choice model estimate for user intention indicators used in adopting Fintech.

Variables	Coefficient	S.E.	Z-ratio	95 % Confidence interval
Social factor	−0.7156	0.8213	−0.87	[-2.3251,0.8940]
Image	0.9292*	0.5043	1.84	[-0.0590, 1.9171]
Perceived behavioural control	0.7385**	0.3341	2.21	[0.0831, 1.3934]
Facilitating condition	0.2080	0.2653	0.78	[-0.3120, 0.7282]
Compatibility	0.5940*	0.3446	1.72	[-0.0815, 1.2695]
Age	0.0255	0.1023	0.25	[-0.1749, 0.2260]
Female	1.8677	3.2290	0.58	[-4.4620, 8.1983]
Log of Income	−0.2282	0.3724	−0.61	[-0.9582, 0.5018]
Education	−0.0435	0.0563	−0.77	[-0.1540, 0.0669]
Self-employed	2.1686**	0.9560	2.27	[0.29486, 4.0424]
Employee	0.4276	0.4266	1.00	[-0.4085, 1.2637]
Experience	−1.0734	0.7425	−1.45	[-2.5288, 0.3819]
Use of fintech	1.1496*	0.8505	1.76	[-0.1708, 3.1630]
Voluntary	−0.5748	0.7205	−0.80	[-1.9870, 0.8373]
Social factor*female	−0.1148	0.4153	−0.28	[-0.9289, 0.6992]
Image*female	1.023***	0.2772	3.69	[0.4795, 1.5664]
Perceived behavioural control*female	−0.9727**	0.4569	−2.13	[-1.8682, −0.0772]
Facilitating influence*female	0.5750	0.4357	1.32	[-0.2791, 1.4291]
Compatibility*female	−0.4277	0.4631	−0.92	[-1.3354, 0.4798]
Facilitating influence*experience	0.05950	0.0633	0.94	[-0.0647, 0.1837]
Compatibility*experience	0.2094**	0.0968	2.16	[0.01962, 0.3993]
Perceived behavioural control*experience	0.02280	0.1072	0.21	[-0.1874, 0.2330]
Social influence*age	0.02217	0.0215	1.03	[-0.0200, 0.0643]
Image*age	−0.0297 **	0.0131	−2.26	[-0.0555, −0.0039]
N = 237	LR χ^2 (24) = 222.33; Prob (χ^2) = 0.000; Pseudo R^2 = 0.4406; Log likelihood = −141.1156.			

S.E. = Standard errors; ***p < 0.001, **p < 0.05, *p < 0.1.

Table 5
Blinder-Oaxaca decomposition.

Threefold decomposition				Twofold decomposition			
User intention	Coefficient	S.E.	P-value	User intention	Coefficient	S.E.	P-value
Differential				Differential			
Male	2.3956***	0.0803	0.000	Male	2.3956***	0.0762	0.000
Female	2.0958***	0.0704	0.000	Female	2.0958***	0.0689	0.000
Difference	0.2997***	0.1072	0.005	Difference	0.2997***	0.1027	0.004
Decomposition				Decomposition			
Endowments	0.1647**	0.0837	0.049	Explained	0.1489*	0.0784	0.057
Coefficients	0.2601**	0 .1132	0.022	Unexplained	0.1507**	0.0751	0.042
Interaction	−0.1252	0.10399	0.228				
Number of observations: 237							

S.E. = Standard errors; ***p < 0.001, **p < 0.05, *p < 0.1.

shows that females would have been able to reduce the 86.78 % gap in behavioural intention to adopt Fintech if they had had the same coefficients as the male group. The interaction portion of the gap shows that when endowments and coefficients occur simultaneously, the female gap in behavioural intention is reduced by 41.78 %, but is statistically insignificant. In addition, the twofold decomposition (Table 4) shows decomposition results in which the explained factor (the endowment effect) contributes to the mean difference (0.2997) by 49.68 % (0.1489/0.2997), and the unexplained component, also called the discrimination effect, contributes to the mean difference by 50.28 % (0.1507/0.2997). Therefore, up to 49.68 % of the gap in behavioural intention to adopt Fintech could be reduced if females had the same individual characteristics or explanatory variables as the males. Alternatively, the 50.28 % gap in the behavioural intention derived from the discrimination or the unobserved variables.

The detailed decomposition results in Table 6 show that social factors, perceived behavioural control, experience, and voluntary use of Fintech are statistically significant predictors that individually contribute to the differences in the explained part (endowment), whereas image, employee status, self-employed professions, voluntary use, trust (in the case of providing accurate technology quality inspection certificates) in a national authority, trust in a private authority, trust in an international authority, and equal trust (trust in all authorities equally) were found to have individually and statistically contributed to the mean differences in the unexplained part (discrimination effect). If females had the same social influence, perceived behavioural control, experience, and voluntary use as the male group, this could have reduced the gap in FUI, derived from the endowment difference, by 15.72 % (0.0234/0.1489), 24.45 % (0.0364/0.1489), 46.27 % (0.0689/0.1489), and 34.49 % (0.0513/0.1489) respectively. Likewise, if females had the same image coefficient as the males, while keeping their endowments fixed, the discrimination gap in FUI would have been reduced by 334.31 % (0.5038/0.1507). However, the voluntary use variable was found to positively contribute to the endowment difference, while negatively contributing to unexplained difference, indicating an extreme case which requires further investigation.

Furthermore, keeping their endowments constant, if females had the same coefficients, deriving from trust in national authorities, trust in the private authorities, trust in international authorities, and trust in all authorities equally, the gender gap in behavioural intention to adopt Fintech would have been reduced by 146.85 % (0.2213/0.1507), 37.69 % (0.0568/0.1507), 490.78 % (0.7396/

Table 6
Twofold detailed decomposition.

Variables	Explained			Unexplained		
	Coefficient	S.E.	P-value	Coefficient	S.E.	P-value
Social factor	0.0234*	0.01416	0.097	−0.2104	0.3724	0.572
Image	−0.0026	0.0058	0.654	0.5038*	0.2738	0.066
Perceived behavioural control	0.0364*	0.0205	0.077	−0.4517	0.5871	0.442
Facilitating condition	0.0012	0.0140	0.931	0.5123	0.4074	0.209
Compatibility	−0.0024	0.0281	0.930	−0.1175	0.5304	0.825
Age	0.0012	0.0046	0.786	0.3861	0.3031	0.203
Log of Income	−0.0064	0.0083	0.437	2.1564	1.7470	0.217
Education	−0.0027	0.0072	0.708	−0.3688	0.3527	0.296
Employee	0.0345	0.0337	0.306	−0.6608***	0.1794	0.000
Self-employed	−0.0392	0.0339	0.247	−0.2543***	0.0928	0.006
Experience	0.0689*	0.4039	0.088	0.0700	0.118	0.555
Voluntary use	0.0513**	0.0250	0.040	−0.4882**	0.2111	0.021
Mandatory use	0.0044	0.0184	0.811	−0.0491	0.0303	0.106
Registered club member	0.0045	0.0095	0.631	−0.0876	0.0793	0.269
Local certificate	0.0089	0.0130	0.494	0.0307	0.0210	0.145
National certificate	−0.0050	0.0167	0.762	0.2213***	0.0811	0.006
Private certificate	−0.0248	0.0207	0.231	0.0568*	0.0304	0.062
International certificate	0.0049	0.0196	0.803	0.7396***	0.1780	0.000
All equal	−0.0076	0.01254	0.540	0.1896***	0.0689	0.006
Constant	–	–	–	−2.027	1.6830	0.228
Total	0.1489*	0.0782	0.057	0.1507**	0.0739	0.042

S.E. = Standard errors; ***p < 0.001, **p < 0.05, *p < 0.1.

0.1507), and 125.81 % (0.1896/0.1507) respectively. Conversely, if females had the same coefficients as males for the variables of employee status, being self-employed and voluntary use of Fintech, the UI of females for Fintech would have been reduced, meaning that the gender gap would have reduced further by 438.49 % (0.6608/0.1507), 168.75 % (0.2543/.1507), 323.95 % (0.4882/0.1507) respectively. In other words, the explanatory variables such as employee status, being self-employed, and voluntary use reduced the FUI gap between males and females in favour of females.

5. Discussion

The aim of the study was to investigate the impact of social influences, facilitating influences, and sociodemographic variables on FUI. To this end, an Ologit model was employed. A B–O decomposition model was then used to examine the gender gap in FUI. As the findings from the ologit model (see Table 2) show, image tends to be positively related to FUI. We argue that when individuals perceive that Fintech use will enhance their social status and image in society or at the workplace, they will have a positive attitude toward Fintech adoption. Moore and Benbasa [14] posit that image influences people's adoption of new technology. Specifically, it has a strong influence on females' use of Fintech, and access to financial services enhances women's empowerment and position in the family [61], strengthening their image. However, it was negatively modified by the age variable in relation to FUI. It may be that older people face difficulties because of the complexity of using technology [62], and they may think that the adoption of Fintech will not influence their social status; instead, their social status or image comes from other factors such as wisdom, achievement and experience. As a result, their FUI is negatively influenced, as opposed to that of young people.

According to the theory of diffusion and innovation, compatibility is a factor that influences the adoption of new technology (innovation) [63]. Therefore, compatibility affects FUI positively, as people find that Fintech provides services consistent with their financial needs. Users' experience interacts with compatibility positively in influencing Fintech adoption. When fintech users perceive positive experience from desired and innovative services, as reflected in compatibility, this results in positive FUI. Barbu et al. [64] argue that customer experience in Fintech is positively influenced by perceived value, customer support, assurance, and innovativeness. Experience interacts with compatibility positively to influence Fintech adoption. Accordingly, user PBC shows a positive impact on Fintech adoption. Generally, people tend to display positive behavioural intentions when they have sufficient knowledge and support regarding the use of Fintech. Although PBC shows positive UI, it is negatively influenced when it interacts with females. This may happen because women are more risk-averse to Fintech [65] and have lower objective financial knowledge than males [66].

Of the sociodemographic variables, self-employed people are more likely to intend to use Fintech. Evidence shows that insufficient documents to open a bank account and the distance to banks hinder access to financial services [12]. In Bangladesh, 40.07 % of the labour force do not have an account in order to enjoy financial services [67]. As stated, the self-employed find Fintech to be the most convenient way to obtain financial services; as a result, they may show positive FUI. Wang et al. [68] argue that trust in services and structural assurance (safeguards such as regulations and guarantees) positively influence the continued intention to use fintech services. Accordingly, existing users have shown a positive intention to use Fintech in the near future. However, according to the findings from the detailed decomposition, discrimination is largely driven by the image variables. Discrimination would have been significantly reduced if females had had the same image coefficient as males. A reason for this could be attributed to traditional gender-based roles. For example, in Bangladesh a male family member usually handles the financial aspects or undertakes financial decisions, while females play roles in household activities. Therefore, women do not believe as strongly as men that using Fintech may enhance their status in the family or society, as they have less involvement in the financial aspects of their family.

6. Conclusion and implications

Despite its significance, few studies have examined the effect of social and facilitating influences and sociodemographic variables on user intention towards fintech. Furthermore, very little research has addressed the gender gap in Fintech user intention with social and facilitating influences. Consequently, the study was first conducted to measure the impact of social and facilitating influences, along with the relevant sociodemographic variables, on Fintech user intention. An ordered logit model was employed to examine the user intention to adopt Fintech, thus contributing a new method to the literature. The results demonstrate that image, perceived behavioural control, and compatibility are the significant predictors of behavioural intention towards Fintech. Image is a more significant variable in influencing females' user intention positively, while perceived behavioural control affects such intention negatively. The self-employed and existing users are more likely to use Fintech.

In relation to the findings from the managerial perspective, the study demonstrates that user image is positively related to fintech adoption, and that the relationship becomes stronger with regard to women's user intention. Therefore, the authorities should promote Fintech services in social media or other mainstream media, pointing out the facilities provided by such services. In doing so, agents should prioritise women who use fintech services rather than those who do not in the provision of government services, encouraging women to understand that Fintech enhances their social status. Second, perceived behavioural control was found to be a positive factor in Fintech adoption, but it becomes a negative predictor in influencing the user intention of females. To address this divergence, the government should ensure the security of personal information, shield women against data breaches, and strengthen cyber security so that women feel they have control over Fintech and perceive less risk when using the services. The authorities should foster a regulatory environment that supports innovation and ensures Fintech service providers adhere to security and privacy standards, thus leading to trust and credibility, which may help change women's negative perceived behavioural control. Additionally, when Fintech becomes consistent with existing financial services and needs, individuals will positively adopt it. In this case, the government could collaborate with traditional financial institutions and Fintech to introduce more innovative and comprehensive financial services, such as blockchain-driven ones that are coherent with consumers' convenience and financial needs and at a low cost. Moreover, the government should take the initiative to increase consumers' financial and technological literacy, making Fintech usage more convenient in line with their technological knowledge.

Third, a significant contribution of the study is that it shows that there is a gender gap in Fintech user intention. According to the findings, such discrimination is largely driven by users' image and trust in Fintech. If females had the same image and trust coefficient as males, the discrimination would decline significantly. Based on the findings, the paper has managerial implications. Reducing the gender gap in Fintech adoption would help the government achieve SDG goal 5 (i.e., Achieve gender equality and empower all women and girls). Reducing the Fintech gender gap would not only ensure gender equality, but also ensure the financial inclusion of women, which would have a positive effect on economic development. Furthermore, SDG goal 10 advocates reduced inequalities within and among countries. In this matter, increasing women's participation in Fintech adoption would prompt economic inclusion and empower those women lagging behind in developing and emerging societies. The authorities could initiate workshops and educational programmes to enhance knowledge and the benefits of fintech services, which may encourage women to use them. Agents could also address the gender gap; for instance, by encouraging diversity in the leadership of Fintech services. Gaining women's trust in inspection certificates would reduce the gender gap; therefore, policymakers could compel Fintech service providers to comply with customer data and transaction security and privacy. Additionally, national and international authorities should focus on females' greater privacy concerns when inspecting the quality of technology provision services.

Although the decomposition did not consider the different distribution of outcomes among the individuals in each group, and only provides information about the differences in mean predicted outcomes between the two groups, it could be applied in the gender gap analysis in an effort to identify the contribution of each unequally distributed factor, as well as their different effects on the gap. The extent to which the average results vary according to changes in each factor could therefore be specified, while assuming that the other factors remain constant. Nevertheless, the implications of the study are subject to certain limitations. For instance, the impact of two key variables on Fintech adoption, user performance and effort expectancy, were not included in the model. Future study should measure other cities of Bangladesh with a large sample, to check the validity of the model established in this research.

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CRediT authorship contribution statement

Mohammed Ziaul Hoque: Writing – review & editing, Writing – original draft, Supervision, Software, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Nazneen Jahan Chowdhury:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition, Data curation. **Al Amin Hossain:** Writing – review & editing, Visualization, Validation, Software, Resources, Project administration, Investigation, Formal analysis. **Tanjim Tabassum:** Visualization, Validation, Software, Resources, Project administration, Investigation, Data curation.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e23457.

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